Title:

Chemical map–based prediction of nucleosome positioning using the

Bioconductor package nuCpos

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Abstract

Background:

Methods for predicting nucleosome positioning include bioinformatics,

biophysical, and combined approaches. An advantage of bioinformatics

methods, which are based on *in vivo* nucleosome maps, is the use of natural

sequences that may contain previously unknown elements involved in

nucleosome positioning *in vivo*. The accuracy of such prediction attempts

reflects the genomic coordinate resolution of the nucleosome maps applied.

Thus, nucleosome maps constructed using *Micrococcus* nuclease (MNase),

which has a strong preference for A/T-rich sequences, may not be appropriate

for this purpose. In addition to MNase seq–based maps, base pair–resolution

chemical maps of *in vivo* nucleosomes from three different species (budding and

fission yeasts, and mouse) are currently available. However, these maps have

yet to be integrated into publicly available computational methods.

Results:

We developed a Bioconductor package (named nuCpos) that uses chemical

maps to train duration hidden Markov models (dHMMs) to predict *nuc*leosome

*pos*itioning. The accuracy of chemical map–based prediction was higher than

that of the previously developed MNase seq–based approach. With our method,

predicted nucleosome occupancy reasonably matched *in vivo* observations and

was not affected by A/T nucleotide frequency. Effects of genetic alterations on

nucleosome positioning that had been observed in living yeast could also be

predicted. In addition to dHMM-based prediction, nuCpos can calculate

individual histone binding affinity (HBA) scores for given 147-bp sequences to

examine their suitability for nucleosome formation. Local HBA scores for 13

overlapping nucleosomal DNA subsegments can also be calculated. HBA and

local HBA scores for various sequences agreed well with previous *in vitro* and *in*

vivo studies. Furthermore, our results suggest that nucleosomal subsegments

that are disfavored in different rotational settings contribute to the defined

positioning of nucleosomes.

Conclusions:

Our results demonstrate that chemical map–based statistical models are

beneficial for studying nucleosomal DNA features. Studies employing nuCpos

software can enhance understanding of chromatin regulation and the

interpretation of genetic alterations and facilitate the design of artificial

sequences. nuCpos is freely available from Bioconductor under the GPL-2

license.

Keywords:

63 nucleosome, prediction of nucleosome positions, dHMM, HBA, local HBA,

64 translational and rotational settings, nucleosomal DNA subsegments

Background:

The nucleosome is a structure in which a ~147-base pair (bp) double-stranded DNA forms a left-handed super-helix to wrap a histone octamer consisting of two copies of histones H2A, H2B, H3, and H4 [1-3]. The positioning of nucleosomes along genomic DNA sequences affects various biological events, including transcription, DNA replication and repair, and chromosome segregation [4]. The importance of nucleosome positioning has prompted the development of computational methods to predict nucleosome positions along a given DNA sequence [5]. These methods are classified into three groups: biophysical, bioinformatics, and combined [5, 6]. Most biophysical methods are based on the structures of reconstituted nucleosome core particles (NCPs) such as NCP147, which contains a palindromic 147-bp sequence with intrinsic positional stability [3, 7, 8]. The use of palindromic sequence optimized for homogeneous nucleosome reconstitution and the highest resolution of the structure contributed greatly to the development of prediction algorithms. However, relying on the representative structure itself could also be a potential weakness, as there could be unrecognized natural intra-nucleosomal DNA elements that mediate specific physiologic functions in cells.

Studies using reconstituted nucleosomes other than NCP147 have provided many insights into nucleosome organization. In particular, studies using derivatives of the Widom 601 sequence [7] demonstrated the importance of intra-nucleosomal DNA elements from a physiologic context. When a nucleosome with this sequence is placed before elongating RNA polymerase II, the nucleosome acts as a polar barrier to transcription [9]. In this scenario, the polymerase coming from the right side of the sequence pauses in a manner dependent on an element called R3, which is found at the superhelical location (SHL) −2.5 to the left and strongly contacts the histone core [10, 11]. Structural studies demonstrated that a palindromic sequence consisting of two copies of the left-half of the Widom sequence yields a high-resolution X-ray structure, whereas the nucleosome with a right-half palindrome is less stable and yields poor crystals [12, 13]. Efficient reconstitution with the left-half sequence was confirmed in another study [14]. Indeed, the positioning power of the left-half sequence is exploited in reconstitution studies that require nucleosomes at targeted positions [15, 16]. However, why the left- and right-half sequences

behave differently and how the left-half sequence determines the rotational and
translational settings remain to be fully elucidated.

In contrast to the biophysical prediction methods, bioinformatics
methods are based on maps of *in vivo* nucleosomes determined using
high-throughput sequencing techniques. *In vivo* nucleosomes contain various
DNA elements that should not necessarily be appropriate for nucleosome
formation (e.g., protein-coding sequences and recognition motifs for
transcription factors). In addition, various types of *trans*-acting factors (e.g.,
transcription factors, histone chaperones, and chromatin remodeling factors) are
known to regulate nucleosome positioning in cells, as reviewed elsewhere
[17-19]. Furthermore, similarity in the usage of dinucleotides at each
superhelical turn in the nucleosome may help nucleosomes position redundantly
along the genomic coordinates with a periodicity of approximately 10 bp [20-23].
Indeed, *in vivo*, most nucleosomes exhibit redundant positions on the genome
[24-26]. The use of complex, natural nucleosomal sequences may cause
difficulty in the interpretation of prediction results; however, use of these
sequences may also lead to unexpected findings that enhance understanding of
nucleosome-based regulation.

A weakness of currently available bioinformatics methods is that the
statistical models are constructed based on *in vivo* nucleosome maps generated
using *Micrococcus* nuclease (MNase) digestion followed by high-throughput
sequencing (MNase-seq). MNase digests linker DNA that connects NCPs,
allowing researchers to obtain nucleosomal DNA that has been protected from
enzymatic digestion. In MNase-seq experiments, DNA fragments of
mono-nucleosome size (~150 bp) are sequenced and mapped to the reference
genome. However, as MNase strongly prefers A/T-rich sequences, unwanted
digestion of A/T-rich nucleosomal sequences and less-effective digestion of
G/C-rich linkers may occur, leading to variation in nucleosome fragment size [19,
27]. Because of this enzymatic bias, precise determination of the genomic
coordinates of *in vivo* nucleosomes using MNase-seq (i.e., dyad base calling) is
challenging.

One bioinformatics method considered successful in a thorough
comparative study [6] is NuPoP, which is built upon a duration hidden Markov

model (dHMM) that considers information regarding both the nucleosome and
linker DNA [28]. NuPoP enables the prediction of nucleosome positioning in nine
different species by rescaling the base composition of both the nucleosome and
linker models for the budding yeast *Saccharomyces cerevisiae* with those of
target organisms. The budding yeast models are generated using an
MNase-seq–based nucleosome map by considering the central base of each
nucleosomal fragment of varying length the dyad base [28]. This may particularly
affect construction of the time-dependent statistical model for the nucleosome
state, which ideally requires that the dyad bases be determined at bp resolution.
The construction of the linker model, which requires extraction of linker
sequences as genomic sequences not covered by nucleosomes, may also be
affected. Thus, although selecting the MNase-seq–based map was the best
practice at the time of the software's development, the prediction results output
provided by NuPoP can be biased by both the enzymatic preference of MNase
and the difficulty of dyad base calling.
In order to examine the suitability of a given 147-bp sequence for
nucleosome formation using the NuPoP algorithm, a histone binding affinity
(HBA) score, also referred to as a 'nucleosome affinity score', is calculated [28].
According to the authors' definition, this score should ideally predict the
rotational setting of nucleosomes along the genome. However, this capability
would only be expected when the *in vivo* nucleosome map used for construction
of the statistical model is at bp resolution. This means that the low coordinate
resolution of the MNase-seq–based map could cause ambiguity in the prediction.
Indeed, at the implementation level, NuPoP smooths raw HBA scores using a
moving average of a 55-bp window and standardizes the scores on a per
sequence basis before outputting the processed HBA scores. This prevents
software users from examining the actual HBA score for each genomic
coordinate to see if the 147-bp sequence of interest is suitable for nucleosome
formation.
A breakthrough in nucleosome mapping occurred with the development
of a method for site-directed chemical cleavage of nucleosomal DNA followed by
high-throughput sequencing [24, 29]. This technique, called chemical mapping,
was first applied to budding yeast and then to the fission yeast

Schizosaccharomyces pombe and embryonic stem cells of the house mouse,

Mus musculus [24-26, 30, 31]. In cells expressing histone H4 with an S47C

amino acid substitution located near the nucleosome center, nucleosomal DNA

is specifically cleaved. By examining the cleavage sites, previous studies

determined the dyad positions of *in vivo* nucleosomes in the three species at bp

resolution [24-26]. In addition to the histone H4-S47C approach, chemical

mapping of nucleosomes using a histone H3 mutation (Q85C) determined the

precise positions of −1 and +1 nucleosomes for protein-coding genes [27].

Molye-Hyerman and colleagues demonstrated that dHMMs trained with

chemical maps can roughly predict the phasing pattern of nucleosome

occupancy in budding and fission yeasts [25]. For an unknown reason, they

used a uniform distribution as the linker length distribution in the calculation. In

order to predict the relative positions of nucleosomes using the dHMM as it was

originally proposed, a non-uniform, experimentally obtained distribution of linker

lengths should be used. Most importantly, the bp-resolution chemical maps have

not yet been implemented in publicly available software for prediction of

nucleosome positioning.

One goal of nucleosome positioning prediction is *in silico* reproduction

of *in vivo* observations, preferably at the locus level. If this goal is achieved,

predicting the effects of genetic alterations on nucleosome positioning and

prediction-based engineering of nucleosome-forming and -depleted sequences

would also be practical. In this regard, budding and fission yeasts would serve

as preferable model organisms, because nucleosomes formed on native and

modified sequences *in vivo* have been precisely mapped [32-37]. These

nucleosomes are suitable for *in silico* reproduction of *in vivo* observations.

Importantly, for the currently available bioinformatics method NuPoP, the

reliability of locus-level nucleosome prediction has seldom been demonstrated,

despite its wide use in previous studies [38-47].

In this study, we developed a nucleosome positioning prediction

method that utilizes available chemical maps of three species for construction of

dHMMs. We show that the prediction accuracy of chemical map–based models

is higher than that of MNase-seq–based models. The chemical map–based

models appear to recognize appropriate sides of DNA strings as histone-DNA

contact surfaces. The effects of genetic alterations on nucleosome positioning

previously observed in living yeast cells were reasonably reproduced *in silico*,

suggesting that this software is useful for chromatin engineering and

interpretations of mutation effects. We found that the prediction accuracy for

mice was lower than that for yeasts, which should be acknowledged by software

users. Our software, nuCpos, is available at the Bioconductor website

(https://doi.org/doi:10.18129/B9.bioc.nuCpos).

Results:

Chemical map–based prediction of nucleosome positioning in yeasts

In order to determine whether the bp-resolution chemical maps are suitable for

predicting nucleosome positioning, we trained dHMMs with the nucleosome

maps determined with H4-S47C–dependent DNA cleavage (see **Methods**).

Linker length distributions derived from the chemical maps, which were

implemented in our method (nuCpos), exhibited a 10-bp periodicity, as

previously reported [24-27, 48] (**Additional file 1: Figure S1**). In contrast, linker

length distributions of the MNase-seq–based method, NuPoP, did not exhibit

such periodicity, reflecting the difficulty of mapping nucleosomes at bp resolution

using MNase digestion.

First, we predicted nucleosome positioning in the genomes of budding

and fission yeasts (denoted 'Sc' and 'Sp', respectively, in **Figure 1**) with models

that were constructed with *in vivo* nucleosome maps of target species (hereafter

referred to as "matched-species prediction"). Based on the prediction results, we

drew receiver operating characteristic (ROC) curves (**Figure 1A**, upper panels)

and calculated area under the curve (AUC) scores (**Additional file 1: Table S1**).

Here, only the predicted nucleosomes for which the dyad bases matched those

of *in vivo* nucleosomes at a resolution of 1 bp were considered to be correctly

predicted (see **Methods**). The prediction performance of the MNase-seq–based

model for unique (representative) budding yeast nucleosomes as determined by

AUC was 0.532, and it was 0.526 for redundant nucleosomes (**Figure 1A**,

Target: Sc, Model: Sc, blue). Prediction for the fission yeast genome resulted in

similar results (**Figure 1A**, Target: Sp, Model: Sp, blue). In contrast, better

prediction performance was observed with the chemical map–based model

(**Figure 1A**, upper panels, red). In both yeasts, AUC scores for unique

nucleosomes (budding yeast, 0.751; fission yeast, 0.743) were more than 0.07

points higher than those for redundant nucleosomes (**Additional file 1: Table**

S1). These results suggest that the chemical map–based models better predict

the suitability of a given sequence for nucleosome formation, as unique

nucleosomes are known to have sequences preferred for nucleosome formation

[24, 25].

Prediction performance was also evaluated using cross-species

models; nucleosome positioning in the target genomes was predicted using

models constructed with nucleosome maps of different species. Using the

budding yeast chemical model for prediction of nucleosome positioning in the

fission yeast genome (**Figure 1A**, Target: Sp, Model: Sc, red) resulted in lower

AUC scores for unique and redundant nucleosomes (0.667 and 0.626,

respectively) in comparison with the matched-species scores (**Additional file 1:**

Table S1). A reciprocal prediction with the budding yeast genome and the fission

yeast chemical model resulted in similar scores (**Figure 1A**, Target: Sc, Model:

Sp, red). These results indicate that the species of the nucleosome map from

which the model is constructed must be matched to the prediction target species

for optimal prediction results. For MNase-seq–based predictions,

matched-species and cross-species predictions performed similarly (**Additional**

file 1: Table S1 and Figure 1A, compare blue lines in upper and bottom panels).

Interestingly, these MNase-seq–based scores were much lower than those

obtained from chemical map–based cross-species predictions. These results

thus highlight the usefulness of chemical map–based models and indicate that

nucleosome-forming sequences exhibit similar properties in both types of yeast,

as previously reported [25].

Ideally, prediction results should be evaluated at a 1-bp resolution, as

done above, because if nucleosomes can be predicted at such a high resolution,

it might be possible to discern the rotational settings of given nucleosomes. As

the resolution of the chemical maps that we used for model construction could

be 1-2 bp or lower, the resolution of the prediction results would be expected to

be at a similar level. Indeed, the distance between chemically predicted

nucleosomes and the nearest *in vivo* nucleosomes was generally 0 bp (located

at the same position) or 1 bp (located at the juxtaposed nucleotide positions)

(**Figure 1B**, left panel). In order to determine the appropriate resolution for

examining prediction results, we calculated the matching rate between predicted

and *in vivo* nucleosomes with stepwise widening of the matching window

(**Additional file 1: Figure S2**). Here, we defined the matching window as the

allowable distance between nucleosomes regarded as matched. In chemical

map–based predictions (nuCpos), the matching rate doubled to over 50% when

the matching window was widened from 0 bp (1-bp resolution) to 1 bp (2-bp

resolution) (**Additional file 1: Figure S2**, red lines). However, the rate did not

markedly increase upon further widening of the matching window, suggesting

that the chemical models distinguish the histone-facing side of the DNA string.

In MNase-seq–based predictions (NuPoP), by contrast, the matching

rate increased gradually as the matching window was widened from 0 to 9 bp

(**Additional file 1: Figure S2**, blue lines). The matching rate drew a very loose

anti-S shape, suggesting that the MNase-seq–based model still recognized the

histone-facing side of the DNA string, but only to a small extent. We also noticed

that a substantial population of nucleosomes predicted with the

MNase-seq–based model was positioned approximately 5 nucleotides away

from the *in vivo* nucleosomes (**Figure 1B**, right panel, marked with a blue

horizontal bar). These observations suggest that the MNase-seq–based model

has difficulty in discriminating rotationally mispredicted nucleosomes.

Considering these results, we concluded that prediction results should be

evaluated at 2-bp resolution, as further widening of the matching window would

increase the misprediction rate.

The left panel of **Figure 1C** presents the evaluation of matched-species

predictions at 2-bp resolution. When the budding yeast MNase-seq–based

model (NuPoP) was applied to the prediction of nucleosome positioning in the

budding yeast genome (Target: Sc, Model: Sc), only 3.2% and 12.6% of the

nucleosomes on the most probable (Viterbi) path matched *in vivo* unique (red)

and redundant (orange) nucleosomes, respectively. When the fission yeast

model was applied to the prediction of nucleosome positioning in the fission

yeast genome (Target: Sp, Model: Sp), the MNase-seq–based model scored

2.7% and 11.0%, respectively. In contrast, when the budding yeast chemical

map–based model (nuCpos) was used for predictions (Target: Sc, Model: Sc),

23.5% and 50.9% of the nucleosomes on the Viterbi path matched unique and

redundant nucleosomes, respectively. For the fission yeast (Target: Sp, Model:

Sp), the corresponding scores were 25.5% and 54.2%, respectively. Thus, with

the chemical map–based models, over half of the nucleosomes predicted as

being on the Viterbi path are present in living cells at exactly the same positions

or at the juxtaposed nucleotide positions. In the chemical maps of budding and

fission yeasts, *in vivo* unique nucleosomes accounted for 19.6% and 17.8%,

respectively, of all redundant nucleosomes [24, 25]. Thus, in the

MNase-seq–based predictions, enrichment of unique nucleosomes on the

Viterbi paths was only 1.3- and 1.4-fold, respectively. In contrast, the chemical

map–based predictions exhibited 2.4- and 2.6-fold enrichment, respectively. The

higher enrichments suggest that chemical map–based models better distinguish

sequences favorable for nucleosome formation, compared with

MNase-seq–based models [24, 25].

The right panel of **Figure 1C** presents the evaluation of cross-species

predictions at 2-bp resolution. When the fission yeast MNase-seq–based model

(NuPoP) was used to predict nucleosome positioning in the budding yeast

genome (Target: Sc, Model: Sp), 12.7% of the nucleosomes on the Viterbi path

matched *in vivo* redundant nucleosomes. Prediction in the fission yeast genome

with the budding yeast model (Target: Sp, Model: Sc) scored 10.8%. When the

chemical map–based model (nuCpos) was used for cross-species predictions,

greater proportions of predicted nucleosomes matched *in vivo* redundant

nucleosomes: 36.7% (Target: Sc, Model: Sp) and 37.1% (Target: Sp, Model: Sc).

Thus, although the prediction accuracy tends to decrease, cross-species

predictions using chemical map–based models appear to produce better results

than MNase-seq–based models.

Prediction of *in vitro* reconstituted nucleosome positions

The evaluations described above suggested that chemical models perform

better in the prediction of rotational settings. To confirm this observation, we

compared HBA scores calculated along the original 282-bp Widom 601

sequence [7] with the chemical map–based and MNase-seq–based models

(**Figure 2A**). As mentioned in the Introduction section, non-smoothed HBA

scores are expected to predict the rotational setting of nucleosomes if the

resolution of the nucleosome map used for model construction is sufficiently high.

The original 282-bp Widom 601 sequence contained primer sequences for the

SELEX study at both ends and additional sequences flanking the

nucleosome-forming 147-bp sequence centered at nucleotide position 154 [7].

When analyzed using the chemical map–based model, discrete HBA peaks with

an interval of approximately 10 bp were observed at positions 124, 135, 143,

154, 164, and 175 (asterisks). This periodicity indicated that nearly the same

surface of the DNA string was predicted to be in contact with the histone core in

these potential translational positions. Among these positions, the one with the

highest HBA score corresponds to the translational position of the *in vitro* stable

nucleosome (position 154, orange vertical lines). In contrast, the

MNase-seq–based HBA score was relatively low at position 154, and the peaks

did not exhibit the apparent 10-bp periodicity. Thus, the chemical map–based

model performed better for the prediction of rotational settings, at least when the

Widom 601 sequence was tested.

We also calculated HBA scores along the 485-bp mouse mammary

tumor virus (MMTV) 3'–long terminal repeat sequence (**Figure 2B**). The dyad

bases of two nucleosomes, designated B and A, were located at nucleotide

positions 139 and 335 (–127 and +70 relative to the transcriptional start site),

respectively [49]. At these positions, chemical map–based HBA scores were the

highest within the 50-bp-wide surrounding regions. For nucleosome B,

alternative translational positions with an interval of approximately 10 bp were

suggested (asterisks), probably due to the higher dinucleotide periodicity of

nucleosome B compared with nucleosome A [49]. Note that the periodicity of the

chemical map–based HBA peaks on this natural sequence was not as clear as

seen with the *in vitro*–optimized Widom sequence (**Figure 2A**). We also noticed

that the MNase-seq–based HBA score was highest at position 339, which was

quite near nucleosome-forming position 335. However, the 4-base difference

suggested that the MNase-seq–based model primarily recognized the opposite

side of the DNA string as the histone-contacting surface.

Figure 2C shows the results of HBA calculations for a dinucleosomal

DNA fragment derived from the somatic 5S RNA gene of *Xenopus borealis* [50].

As one of the two nucleosomes occupies a 150-bp region spanning nucleotide

positions 30 to 179 (–70 to +79 with respect to the +1 nucleotide position of the

5S RNA gene), the dyad base should be around nucleotide positions 103 to 106

[50]. In this tandemly joined duplex sequence, the dyad base of the second

nucleosome should be located around positions 300 to 303. The chemical

map–based model revealed potential nucleosomes with their dyad bases at

positions 105 to 107 and 302 to 304, with relatively high HBA scores. Around

these potential dyad positions, 10-bp periodicity of the chemical map–based

HBA was observed (asterisks). Selection of *in vitro* nucleosome-forming

positions from these candidates could be made by linker histones [50, 51]. In

contrast to the prediction with the chemical map–based model, the

MNase-seq–based model did not appear to successfully recognize appropriate

rotational settings, as in the case of the MMTV sequence.

Prediction of *in vivo* nucleosome positions

Next, we calculated HBA scores around budding yeast –1 and +1 nucleosomes

(n=5,542 each) mapped by means of histone H3-Q85C–based chemical

cleavage [27]. As shown in **Figure 3A**, mean HBA scores calculated using both

models exhibited a periodicity with a 10-bp interval. However, the amplitude of

the chemical map–based HBA scores (red) around the tested nucleosomes was

larger than that of the MNase-seq–based HBA scores (blue). This suggested

that the chemical model could clearly distinguish the surface of the DNA string

that interacts with the histone core even when natural genomic sequences were

queried. We found that the chemical map–based HBA scores were highest at

the –1 and +1 nucleosome positions (0 bp). Chemical map–based HBA scores

for the three neighboring translational positions (10, 20, and 30 bp in distance)

relative to the nucleosome-depleted regions (marked with asterisks in **Figure**

3A) remained relatively high despite the gradual increase in the A/T frequency of

the tested sequences (**Figure 3B**). After the A/T frequency reached a plateau

(A/T≈0.64), the chemical map–based HBA scores began to decrease. In

contrast, MNase-seq–based HBA scores at the –1 and +1 nucleosome positions

(0 bp) were already at moderate levels, and they simply decreased as the A/T

frequency increased. Thus, the MNase-seq–based model was adversely

influenced by the enzymatic bias of MNase, whereas the chemical map–based

model was not.

The higher accuracy of chemical map–based models at the genomic

level prompted us to perform a locus-level evaluation of prediction results, using

the budding yeast *TRP1ARS1* minichromosome [34, 36]. On this well-studied,

circular, 1,465-bp DNA, three (numbered I to III) and four (IV to VII)

nucleosomes are interspersed with two nucleosome-depleted regions or

nuclease-hypersensitive regions designated *HSRA* and *HSRB*. *HSRA* includes

the DNA replication origin *ARS1*, whereas *HSRB* is located upstream of the

TRP1 marker gene. At a glance, the chemical map– and MNase-seq–based

model prediction results appeared very different (**Figure 3C**). Each model

suggested eight and seven representative nucleosomes, respectively. Seven of

the eight nucleosomes predicted by the chemical map–based model (**Figure 3C**,

nuCpos) reasonably matched the positions of *in vivo* nucleosomes determined

previously [36]. The only exception was a predicted nucleosome located in

HSRA, in which functional *ARS1* would be occupied by the ARS-binding factor

Abf1 and the origin recognition complex instead of the nucleosome to maintain

this circular DNA across generations [52]. This prediction was reasonable, as

DNA replication origins are known to be covered by nucleosomes when the

subunits of the origin recognition complex or Abf1 are perturbed *in vivo* [52-54].

In this native sequence, the chemical map–based HBA scores

exhibited a periodicity of an approximately 10-bp interval (**Figure 3C**, nuCpos,

and **Additional file 1: Figure S3**). Some nucleotide positions with high HBA

scores were selected by the chemical map–based dHMM as representative

nucleosome positions. As the dHMM considers the linker length distribution as a

major factor affecting nucleosome-linker state transition and does not allow

nucleosomes with shorter DNAs (<147 bp), nucleosome positions tend to be

selected in a limited manner. Although there were many high-HBA positions,

only a few were clearly selected by the dHMM. Thus, although the predicted

occupancy provides a rough image of chromatin state, it should be cautiously

considered. Instead, it should be kept in mind that periodic HBA scores may

contribute to redundant nucleosome positioning *in vivo.*

In contrast to the chemical map–based model, most of the

nucleosomes predicted by the MNase-seq–based model were mislocated

(**Figure 3C**, NuPoP); most of the *in vivo* nucleosome centers (inverted triangles

in figure) were located in predicted linkers or nucleosome ends. This tendency to

mislocate nucleosomes may explain the lower genome-wide prediction accuracy

(**Figure 1**). Importantly, MNase-seq–based HBA scores for this sequence

appeared to mirror the A/T-content over the X-axis (**Figure 3C**, A/T); high-HBA

positions were generally A/T-poor, and low-HBA positions were A/T-rich. In

addition, the local amplitude of MNase-seq–based HBA scores was apparently

lower compared with the chemical map–based model (**Additional file 1: Figure**

S3). These observations also demonstrated that MNase-seq–based model

prediction results are influenced by the A/T preference of MNase. A/T-content

exhibited a similar effect in the MNase-seq–based nucleosome positioning

prediction around the fission yeast *ura4*[+] gene (**Additional file 1: Figure S4**)

[55]. Given these results, we concluded that the chemical map–based models

output better genome-wide and locus-level prediction results.

Prediction of effects of genetic alterations on nucleosome positioning

Next, we examined whether the effects of genetic alterations on nucleosome

positioning could be predicted. In α cells of budding yeast, expression of the

a-specific gene *BAR1* is repressed by *α2*-operator–dependent positioning of the

nucleosome at its promoter, which masks the gene's *TATA* box [32, 35]. The

chemical map–based model perfectly predicted the positioning of this repressive

nucleosome (**Figure 4**, WT). The HBA score for this translational position (0 bp),

which is 82 bp away from the *α2*-operator, was very high (HBA=8.47),

suggesting that repression of the *BAR1* gene is assisted by the intrinsic

suitability of the promoter DNA for nucleosome formation. When a 36-bp

sequence consisting of 12 repeats of CTG is inserted at the center of this

nucleosome, repression of *BAR1* and nucleosome positioning are not affected *in*

vivo [35]. Prediction results agreed that this insertion should not cause

nucleosome depletion (**Figure 4**, [CTG]$_{12}$). Other repeat sequences causing no

transcriptional derepression *in vivo* [35] were also predicted to not cause

nucleosome depletion (**Figure 4**, Sac_5 and Sac_6). It is also known that insertion

of a 30-bp A-stretch or a 10-bp CG (i.e., CpG) repeat sequence inhibits *in vivo*

nucleosome formation and causes derepression of *BAR1* [35]. Interestingly, the

effect of these genetic alterations on nucleosome positioning was reproduced *in*

silico with the chemical map–based model (**Figure 4**, A_{30} and CG_5). We noted

that the disruptive effect of fragment insertion on nucleosome positioning was

more pronounced in predictions than *in vivo* observations. Insertion of a 20-bp

A-stretch, which does not cause complete nucleosome depletion *in vivo*, was

clearly predicted to inhibit nucleosome formation (**Figure 4**, A_{20}). However, in the

case of CG repeat insertion, shortening of the repeat to 8 bp, which satisfies *in*

vivo nucleosome formation [35], was predicted to preserve the capability to form

nucleosomes (**Figure 4**, CG_4). Thus, despite some exceptions, the effects of

genetic alterations on nucleosome positioning can be predicted with the

chemical map–based model.

We also confirmed that the inhibition of nucleosome formation by

telomeric DNA insertion demonstrated in a previous study [56] was also largely

predictable (**Additional file 1: Figure S5**). In budding yeast cells, the fourth

nucleosome of a derivative of the *TRP1ARS1* minichromosome called *TALS* is

formed in a manner dependent on the *α2*-operator [33, 37]. Note that the

chemical map–based model predicted the location of this nucleosome at a

shifted position that unexpectedly would cover the *α2*-operator (**Additional file**

1: Figure S5, WT); the central of the three predicted nucleosomes should have

been centered at nucleotide position 0. The shift may be a consequence of the

relatively low HBA score for the *in vivo* translational position (position 0), where

the nucleosomal DNA contains an artificial sequence of bacterial origin [33, 37].

When telomeric DNA fragments are inserted at the center of the fourth

nucleosome, shorter fragments (hTEL2 and hTEL4) were predicted to not affect

nucleosome positioning. In contrast, longer fragments (hTEL12 and hTEL29)

were predicted to severely compromise nucleosome formation. These prediction

results agreed with previous *in vivo* observations [56]. In addition, sequence

isomers of the telomeric repeat (SI-A6, SI-A12, SI-B6, and SI-B12) were

predicted to not inhibit nucleosome formation, which also agreed with the *in vivo*

experiments [56]. The hTEL6 insertion, which causes nucleosome depletion *in*

vivo, appeared not to affect nucleosome formation in the prediction, suggesting

a limitation of the prediction. Nonetheless, these results suggest that the

chemical map–based models are useful for predicting the effects of genetic

alterations on nucleosome positioning.

Local HBA for nucleosomal DNA subsegments

The successful increase in prediction accuracy and better recognition of

rotational settings with chemical map–based models suggested that the

chemical map–based HBA score for a given 147-bp sequence is a good

indicator of the suitability of that sequence for nucleosome formation. However,

considering that nucleosomal DNA makes contact with histone proteins at each

superhelical location (SHL ±0.5-6.5), we thought that the suitability of

intra-nucleosomal DNA segments for each histone-DNA contact could also be

calculated as "local" HBA scores. In order to implement this idea, we divided a

147-bp whole nucleosomal segment into 13 overlapping nucleosomal DNA

subsegments, designated A through M (**Additional file 1: Figure S6**, See

Methods). Each 20- or 21-bp segment corresponded to two histone-DNA

contact sites, each of which was shared by neighboring segments. For example,

segment B corresponded to SHL –5.5 and –4.5, which were shared by

segments A and C, respectively. We took this overlapping approach because it

remains unclear how surrounding sequences affect histone-DNA contacts.

Calculating local HBA scores is conceptually the same as that of HBA

calculations, which consider the probability of a whole 147-bp sequence to be a

nucleosome [28]. In local HBA calculation, for each intra-nucleosomal segment

of a given 147 bp, the probability of the selected 20- or 21-bp sequence to be

located at that part of the nucleosome and the probability of the same sequence

functioning as a linker are calculated. The log likelihood ratio of these

probabilities is defined as the local HBA score for that segment. Thus, the sum of

local HBA scores for the non-overlapping set of seven 21-bp segments, A, C, E,

G, I, K, and M (147 bp in total), would be nearly equal to the HBA score

calculated for the same 147-bp sequence.

In order to examine whether local HBA scores indicate the suitability of

nucleosomal subsegments for histone-DNA contacts, we used the 282-bp

Widom 601 sequence, which was used for the above HBA analysis (**Figure 2A**),

as a test sequence. At potential translational positions with high HBA scores,

local HBA scores for some segments were very high, as expected (**Figure 5A**,

arrows). However, each 147-bp sequence also contained segments with

relatively low local HBA scores. Interestingly, at translational positions with low

HBA scores (those intervened by the high-scoring HBA positions), some

segments exhibited very low local HBA scores (blue blots in the heatmap). This

tendency was particularly notable for the central segments E through I. The

finding of these low-scoring local HBA segments suggests that sub-sequences

that are disfavored in other rotational settings play a role in determining

rotational settings.

Next, we focused on the 147-bp Widom 601 sequence, of which the

dyad base is located at nucleotide position 154 of the original sequence (**Figure

5A**, red arrow). We chose this sequence because its derivatives are often used

in reconstitution studies, as it forms a homogeneous nucleosome, and because

the left and right halves exhibit different features. In agreement with the

transcription studies mentioned in the Background section [10, 11], local HBA

scores for the 147-bp sequence were highest for segments D and E, both of

which share SHL –2.5, in which the high-affinity R3 element is located (**Figure

5B**, red dots). The region covered by segments D and E (SHL –1.5 to –3.5) are

known to exhibit high permanganate reactivity, which is indicative of DNA

distortion resulting from very strong histone-DNA interaction at these segments

[12]. These data indicate that local HBA scores are useful for evaluating the

suitability of nucleosomal subsegments for histone-DNA contacts.

The overall image of the local HBA for the 147-bp Widom 601

sequence did not change with variations in the terminal sequences for

biochemical handling (**Additional file 1: Figure S7**, 601LR, red dots) [12]. In the

palindromic sequences made of each half, the local HBA landscapes were

conserved compared with that of the original sequence, as expected by their

sequence identity (**Additional file 1: Figure S7**, 601L and 601R, red dots).

Indeed, the left-half palindrome (601L) had four segments with very-high HBA

scores (segments D, E, I, and J) and four other segments with relatively low

scores (A, B, L, and M). The local HBA score for segment G increased from a

low to moderate level following palindromization. In contrast to the left half, the

local HBA scores for the right-half palindrome (601R) were moderate for

segments A through F and H through M and relatively low for segment G. The

absence of segments with very-high local HBA scores in the right-half

palindrome may contribute to the lower salt stability of the reconstituted

nucleosome [12].

When the translational position was shifted along the 282-bp sequence

from nucleotide position 154 to surrounding nucleotide positions ranging from

150 to 158 (**Figure 5C**, –4 to +4 with respect to 154), the local HBA scores for

segments B through I changed dramatically (**Figure 5B**, black dots). However,

such shifting resulted in modest changes at segments J through M, with their

scores remaining at relatively high levels. These observations suggest that

segments J through M in the right-half sequence are generally suitable for

nucleosome formation, which may also be true even when the translational

position is shifted by several base pairs. In other words, segments J through M

do not seem to have intra-nucleosomal disfavored elements that strongly limit

the rotational setting. Reflecting the property of the non-palindromic sequence,

palindromization of the left half yielded six segments (D-F and H-J) that exhibited

the highest local HBA scores at the *in vitro* translational position (**Additional file**

1: Figure S7, 601L, black dots). In addition, the shifting score patterns for

segments C and K suggest that shifting to either side may reduce the sum score.

Thus, the rotational setting of this sequence appears to be determined through

overall suitability for histone-DNA contacts. For the right-half palindrome, only

the central segments with low to moderate local HBA scores (E through I) could

contribute to the rotational setting. This nature might account for the observed

poor crystal development or lower homogeneity [12], as this 'slippery' sequence

could disrupt the uniformity of histone-DNA interactions.

As a comparison, we analyzed the palindromic sequence of NCP147

(**Additional file 1: Figure S7**, NCP147). In this sequence, the local HBA scores

for outer segments A through C and K through M were high, whereas the inner

part (segments D through J) scored lower (red dots). In contrast to the Widom

derivatives, local HBA scores for most of the segments were not high at the *in*
vitro translational position. However, each segment appeared to contribute to
the determination of rotational setting. For example, while the score for segment
B decreased when the translational position was shifted to the left side, that for
segment C decreased when shifted to the opposite side. The same was true for
segments K and L. Similarly, local HBA scores for segments F and H decreased
when the translational position was shifted inward. These observations suggest
that being a palindrome itself helps generate homogeneous nucleosomes by
preventing alternative positioning.
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Local HBA scores for modified nucleosome-forming sequences
The above testing with the sequences previously used in reconstitution studies
suggested that calculating local HBA scores would enhance understanding of
how DNA sequences characterize the nucleosomes formed *in vitro*. This
prompted us to examine whether we could apply local HBA calculations to the
evaluation of intracellular nucleosome formation. González et al. reported that
sequence-based determinants of nucleosome positioning are dispersed across
nucleosomes [55]. One gene that they thoroughly investigated was the fission
yeast gene, *ura4$^+$*. This gene has six representative nucleosomes (designated
+1 to +6) that overlap the coding sequence, five of which were predictable with
the chemical map–based dHMM (**Additional file 1: Figure S4**, nuCpos).
Although the remaining nucleosome (+5) was not clearly observed in the
predicted occupancy plot, there was one position with a relatively high HBA
score that reasonably corresponded to the *in vivo* nucleosome (marked with an
asterisk in the figure). A heatmap of local HBA scores for this gene suggested
that there is an element disfavored for nucleosome formation near the +5
nucleosome (**Figure 6A**, WT, see the blueish slanted line spanning segments A
through M around position 700). Thus, this element may have caused the lower
predicted occupancy of the +5 nucleosome.
González et al. also generated three modified sequences, namely
Dyad, Linker, and Int, for the *ura4$^+$* gene and studied nucleosome positioning on
these sequences *in vivo* [55]. In Dyad and Linker, 51-bp sequences centered to
each nucleosome dyad and each linker, respectively, were replaced with

artificial randomized sequences of the same length. In the sequence Int, two

intra-nucleosomal sequences of each nucleosome (positions from –51 to –24

and 24 to 51) were replaced. According to their report, the occupancy of the +1

nucleosome was markedly decreased in the Dyad sequence, that of the +2

nucleosome was slightly increased in the Dyad and Linker sequences, and the

position of the +3 nucleosome was shifted in the Int sequence [55]. However,

why these changes selectively occur on specific nucleosomes *in vivo* remains

unclear due to a lack of appropriate analytical methods.

A heatmap of local HBA scores for the Dyad sequence clearly showed

that the replacements in this sequence caused a marked decrease in local HBA

scores only around the position of the +1 nucleosome (**Figure 6A**, Dyad, blue

lines not present in the WT map). The heatmap also suggested that the replaced

segment in the +1 nucleosome exerts a strong effect only on the central

nucleosomal subsegments (E through I). Indeed, at the *in vivo* translational

position, the Dyad replacement caused marked decreases in HBA scores

(**Figure 6B**, +1 Nuc., left, compare gray and green lines), and the effect was

limited to the central segments (**Figure 6B**, +1 Nuc., right, asterisks). In contrast,

the 51-bp replacements at other nucleosomal centers did not appear to

dramatically change their suitability for nucleosome formation. As to the +2

nucleosome, we did not observe any supportive signatures that could explain

why the Dyad and Linker replacements slightly increased its occupancy (**Figure**

6A, Dyad and Linker, and **Figure 6B**, +2 Nuc.). We observed that the Int

replacements primarily affected local HBA scores around the position of the +3

nucleosome (**Figure 6A**, Int, see the blueish slanted line spanning segments A

through M). The Int replacement caused decreases in neighboring HBA scores,

and the effect was greatest at segments C and D (asterisks), where local HBA

scores were among the highest (**Figure 6B**, +3 Nuc., compare gray and black

lines). This suggests that the mutation triggers a shift of the nucleosome to a

more suitable position *in vivo*. Giving these results, local HBA score calculation

for nucleosomal subsegments is useful for *in silico* assessment of modified

nucleosome-forming sequences.

Chemical map–based prediction of nucleosome positioning in mice

The improved prediction accuracy of the chemical map–based models in both

yeasts suggested that the prediction accuracy in mice would also be improved. A

big difference between the genomes of yeasts and vertebrates is that the latter

have CG modifications. We observed that the CG dinucleotide frequency in

mouse nucleosomal DNA sequences was much lower than the frequencies of

other SS dinucleotides (each S stands for a C or G nucleotide) (**Additional file**

1: Figures S8A and S8B). Even in yeast nucleosomes, CG was the least

favored dinucleotide, as previously discovered in budding yeast

H2A.Z-containing nucleosomes [23]. This suggests that CG could be targeted by

modification-mediated regulation of nucleosome-forming suitability. After

normalization with the genomic frequency, mouse nucleosomes did not appear

to exhibit a strong bias in CG frequency overall (**Figure 7A**). In detail, when

compared with the two yeasts, the normalized CG frequency in mouse

nucleosomes was relatively low at SHL 0 (**Figure 7B**, marked with a triangle)

and high at the inner parts of some histone-DNA contact sites (asterisks), as well

as some parts of outer regions (gray horizontal lines). This suggests that CG

dinucleotides can affect the formation of murine nucleosomes at these

intra-nucleosomal regions.

We predicted nucleosome positioning in the mouse genome using the

MNase-seq–based and chemical map–based models. Based on the prediction

results, we drew ROC curves and calculated AUC scores (**Figure 7C**). The

prediction performance of the MNase-seq–based model for the unique

nucleosomes measured by AUC was 0.511, and it was 0.509 for the redundant

nucleosomes. As expected, the chemical map–based model performed better

for both unique (AUC=0.711) and redundant (AUC=0.646) nucleosomes.

Matching of the predicted nucleosomes on the Viterbi paths at a 2-bp resolution

also demonstrated the better performance of the chemical map–based model

(**Figure 7D**). In the MNase-seq–based prediction, 1.4% and 11.0% of predicted

nucleosomes matched unique and redundant nucleosomes, respectively. In

contrast, the chemical map–based prediction scored 10.0% and 41.1%,

respectively. Thus, although the accuracy was not as high as in the case of

yeasts (**Figure 1C**, scored over 50%), the chemical map–based model predicted

the suitability of given sequences for nucleosome formation in mice better than
the MNase-seq–based model.

In order to determine whether the mouse chemical map–based model

could better predict the rotational setting of nucleosomes, as shown in the case
of yeasts, we calculated the matching rate between predicted and *in vivo*
nucleosomes with stepwise widening of the matching window (**Additional file 1:**
Figure S9). As expected, the matching rate for MNase-seq–based prediction
increased gradually as the matching window widened. In chemical map–based
predictions, a dramatic increase in matching rate was observed when the
matching window was widened from 0 to 1 bp. However, unexpectedly, the
matching rate also increased gradually as the matching window was widened
further (See **Additional file 1: Figures S2 and S9** for comparison between
species). The shapes of the matching rate curves suggested the chemical
map–based model still distinguished rotational settings to some extent. However,
the mouse chemical model did not appear to be as good at discriminating
rotationally mispredicted nucleosomes compared with the yeast models.
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Discussion:
We developed a chemical map–based computational method for predicting
nucleosome positioning and assessed the prediction results. Training dHMMs
with chemical maps improved prediction accuracy in budding yeast, fission yeast,
and the house mouse, *Mus musculus* (**Figures 1 and 7, and Additional file 1:**
Figures S2 and S9 and Table S1). 41-54% of the predicted nucleosomes on
the Viterbi paths matched those of *in vivo* nucleosomes at 2-bp resolution.
Genome- and locus-level evaluations showed that the software successfully
predicted the positions of representative *in vivo* nucleosomes (**Figures 3 and 4,**
and Additional file 1: Figures S3 and S4). The *in vivo* nucleosomes that were
not predicted as being representative had high HBA scores at reasonably near
genomic positions. Furthermore, we demonstrated that perturbation of
nucleosome positioning associated with genetic alterations could also be
predicted (**Figures 4 and 6, and Additional file 1: Figure S5**). Thus, we

propose that the software nuCpos can be used for predicting nucleosome

positioning and also for engineering of nucleosome-forming sequences.

As expected, the use of chemical maps in prediction led to strict

recognition of rotational settings, which was demonstrated with *in vitro* and *in*

vivo nucleosome-forming sequences (**Figure 2 and Additional file 1: Figures**

S2 and S9). Indeed, chemical map–based HBA scores for the original Widom

601 sequence indicated that the 147-bp sequence centered at nucleotide

position 154 was suitable for nucleosome formation (**Figure 2A**). The *in vitro*

nucleosome positions formed on natural sequences were also predictable at a

rotational level (**Figures 2B and C**); however, the HBA amplitude along these

sequences was smaller than along the *in vitro*–optimized Widom sequence. In

contrast to the chemical map–based models, the MNase-seq–based models

largely failed to recognize rotational settings (**Figure 2 and Additional file 1:**

Figures S2 and S9). This may have been due to the A/T preference of MNase

and the difficulty of dyad base calling in the construction of MNase-seq–based

nucleosome maps [19, 27]. Indeed, the MNase-map–based model simply

predicted A/T-rich regions as nucleosome-depleted regions (**Figure 3 and**

Additional file 1: Figure S4). Therefore, instead of lower-resolution

MNase-seq–based maps, base-pair-resolution chemical maps should be used in

the development of bioinformatics methods to obtain better prediction results.

In the field of synthetic biology, the MNase-seq–based method NuPoP

has contributed to the design of synthetic promoters and terminators [38, 39].

However, some studies reported that the histone binding affinity and predicted

nucleosome occupancy output by NuPoP do not correlate with synthetic

promoter and terminator activity [43, 44]. Differences in the DNA sequences of

the tested synthetic elements may of course account for this discrepancy, as

discussed elsewhere [43, 44]. Clearly, the A/T frequency does affect the

prediction results of NuPoP (**Figure 3 and Additional file 1: Figure S4**). As

demonstrated in the Results section, the chemical map–based method is more

accurate and not affected by the A/T frequency. Thus, we expect that nuCpos is

applicable to prediction-based engineering and more effective for synthesizing

functional elements. Similarly, nuCpos can also be used to examine whether

DNA sequences of interest are suitable for nucleosome formation, as previously

done with NuPoP [46, 47].

Dividing 147-bp nucleosomal DNA into subsegments and calculating

subsegment local HBA scores revealed unexpected landscapes of the tested

nucleosomes. Our study revealed that the Widom sequence had segments that

are both favored and disfavored for nucleosome formation (**Figure 5A**).

Importantly, segments with high local HBA scores in the Widom 601–derived

sequences matched the high-affinity histone-contacting regions (**Figure 5B and**

Additional file 1: Figure S7). Furthermore, the Widom derivatives had

segments exhibiting the highest local HBA scores at the *in vitro* rotational

settings, which was further emphasized by palindromization with the left-half

sequence (**Additional file 1: Figure S7**). In contrast to the left-half sequence,

the right-half sequence contained segments exhibiting relatively high local HBA

scores that did not change markedly with different rotational settings. Thus,

these sequence-specific features may account for the different behavior of the

Widom derivatives in *in vitro* experiments. For the NCP147 sequence, it

appeared that palindromization itself repressed the shifting of rotational settings

(**Additional file 1: Figure S7**). Collectively, our data indicate that local HBA

scores for given sequences provide insights that enhance understanding of

nucleosome features.

Locus-level assessments of prediction results suggested that software

users should not place undue confidence in the predicted nucleosome

occupancy output from chemical map–based models. Indeed, there was a

misplaced nucleosome that occupied the replication origin *ARS1* (**Figure 3**) and

a shifted nucleosome that covered the *α2*-operator (**Additional file 1: Figure**

S5). Also, the +5 nucleosome of *ura4$^+$* was not predicted as a representative

nucleosome (**Additional file 1: Figure S4**). We speculate that these

discrepancies were due primarily to the fact that the models do not consider

involvement of functional DNA elements or transacting factors that regulate

nucleosome formation at specific genomic locations. In other words, chromatin

regions highlighted by the differences in nucleosome occupancy between

prediction and *in vivo* observations could be the targets of future investigations

aiming to uncover region-specific regulatory mechanisms. From another point of

view, software users should keep in mind that the dHMMs consider linker length
distribution but do not consider partial unwrapping of nucleosomal DNA in
calculating probable paths of nucleosome and linker states. Instead, our
observations suggest that HBA scores indicate redundant positioning of
nucleosomes in the cells; HBA scores are simply calculated for a given 147-bp
sequence, independently of surrounding sequences.

In the three species with available chemical nucleosome maps, mouse
genomic DNA undergoes covalent modification of cytosine in CG dinucleotides,
whereas that of budding or fission yeast does not. There is a negative correlation
between CG frequency and nucleosome occupancy in mammalian cells [57]. In
addition, hypermethylation of cytosine is observed when the chromatin of the
mouse *Pou5f1* gene, which encodes the pluripotency factor Oct4, is changed to
a closed state, suggesting a link between DNA methylation and nucleosome
positioning [58-60]. Furthermore, DNA methylation is correlated with
nucleosome occupancy in humans [61]. Indeed, the nucleosome structure itself
has been suggested as necessary for the maintenance of DNA methylation [62,
63]. In addition, many histone variants exist in mice, which might cause
variability in the preferred sequence for nucleosome formation [64-66]. Taking
this species- or mammalian-specific evidence into account, for nucleosome
positioning prediction in mice, statistical models should be better constructed
from the nucleosome map of mice, not by rescaling yeast models, if applicable.

We demonstrated that the prediction accuracy of the chemical
map–based mouse model was apparently lower than that of yeast models
(**Figures 2 and 7**). A disadvantage of mouse prediction is that the chemical map
probably contains substantial numbers of pseudo nucleosomes [26], which could
not be omitted due to the lower cleavage depth than yeasts. As a consequence,
the density of nucleosomes on the mouse genome is one redundant
nucleosome per 3 bp, which is about 10 times higher than yeast values (see
Methods). Thus, we speculate that the accuracy of mouse nucleosome
positioning prediction can be increased if other chemical maps of higher quality
are produced and used for model construction. In human genomics, the
relationship between various phenotypes and genetic variants has been
explored [67-70]. However, the effects of genetic variants on nucleosome

formation in this regard remain to be studied. Now that our study showed that

insertions and replacements that disrupt nucleosomes in yeast cells can be

predictable *in silico*, it is possible that nucleosome-disrupting human mutations

can be found with the aid of chemical map–based predictions. We showed that

cross-species chemical map–based models exhibit relatively high prediction

accuracy compared with MNase-seq–based models (**Figure 1**). Therefore,

before generating high-quality chemical maps for species other than the budding

and fission yeasts, the yeast models can alternatively be applied for the

prediction of nucleosome positioning in those species.

Conclusions:

In this study, we demonstrated that the accuracy of dHMM-based nucleosome

positioning prediction can be substantially increased by using

base-pair-resolution nucleosome maps for model construction. Our prediction

results suggest that chemical map–based models are useful for predicting

nucleosome positioning in wild-type and modified sequences at the locus level.

We also demonstrated that strong histone-DNA contacts in a nucleosome and

their rotational settings can be predicted. Furthermore, as another advantage of

bioinformatics methods, our models indicate that the commonly used Widom

sequence contains subnucleosomal segments that are disfavored, or statistically

very rare, in *in vivo* nucleosomes at their nucleosomal positions in shifted

rotational settings. We expect that our prediction method will provide further

insights that will enhance understanding of nucleosome-based epigenetic

regulation.

Methods:

Software and data sets

Most analyses were performed in the GNU R environment

(https://www.r-project.org, ver. 3.6.1). R packages were obtained from CRAN

(https://cran.r-project.org/) and Bioconductor (http://bioconductor.org/). Chemical

maps for budding yeast, fission yeast, and house mouse (*Mus musculus*)

embryonic stem cells [24-26] were used for model construction and testing the

prediction accuracy. The budding yeast's chemical map in the sacCer2

coordinate was lifted over to the sacCer3 coordinate, as described elsewhere

[36]. The number of unique and redundant nucleosomes in the budding yeast

genome was 67,548 and 344,709, respectively; fission yeast, 75,828 and

425,653; mice, 10,677,016 and 850,701,275. Reference genomes of budding

yeast (R64-1-1), fission yeast (ASM294v2), and mice (mm9/NCBIM37.67) were

used.

Construction of the nuCpos package

The codes for the construction of parameters used in the nuCpos package (ver.

1.2.0) are available online (**https://doi.org/10.5281/zenodo.3362065**). Genomic

regions covered with the 147-bp non-redundant (unique) chemically mapped

nucleosomes and uncovered were defined as nucleosome and linker regions,

respectively. DNA sequences of these regions were used to construct

parameters that were transferred to internal Fortran programs. Nucleosomes of

which dyads were located within 73 bp of the chromosomal ends were omitted.

For construction of the mouse model, hard-masked genomic sequences were

used, and nucleosome and linker regions containing N were omitted before

parameter construction to avoid potential prediction bias caused by repeat

elements. In total, 67,538 nucleosome regions and 50,622 linker regions were

obtained for the budding yeast genome (sacCer3); fission yeast (ASM294v2),

75,826 nucleosome and 46,557 linker regions; mice (mm9), 4,147,972

nucleosome and 2,484,347 linker regions.

We developed an R function designated *predNuCpos*, which predicts

nucleosome positioning based on a dHMM, as previously proposed by Xi et al.

[28]. Like its ancestral function *predNuPoP* in the NuPoP package

(https://doi.org/doi:10.18129/B9.bioc.NuPoP, ver. 1.34.0), *predNuCpos* receives

a DNA sequence of any length, invokes an internal Fortran program, and

outputs the prediction result either in the working directory or in the working

environment of R. In *predNuCpos*, construction of the dHMM is based on

chemical maps, as described below.

Parameters used in the *predNuCpos* function were constructed

according to the NuPoP paper [28] using the functionalities of the Biostrings

package (https://doi.org/doi:10.18129/B9.bioc.Biostrings, ver. 2.52.0). The

parameters were as follows: *freqL*, one-base frequencies for linker regions; *tranL*,

tranL2, *tranL3*, and *tranL4*, 1st- to 4th-order transition probabilities for linker

regions, respectively; *freqN4*, four-base frequencies at the first four nucleotide

positions of nucleosome regions; *tranN4*, time-dependent 4th-order transition

probabilities for nucleosome regions; *Pd*, linker length distribution that ranges

from 1 to 500 bp. Linker sequences of 7-500 bp in length were used for linker

model construction, as described elsewhere [28]. *freqL* and *freqN4* were

obtained using the *oligonucleotideFrequency* function of Biostrings; *tranL*,

tranL2, *tranL3*, *tranL4*, and *tranN4* were obtained using the

oligonucleotideTransitions function of Biostrings. Moving average smoothing

using the *SMA* function of the TTR package

(https://cran.r-project.org/package=TTR, ver. 0.23-4) at a 3-bp window was

applied to the 4th-order transition probability parameter *tranN4* and to the linker

length distribution parameter *Pd*. The parameters used in *predNuCpos* were

also used in another function *mutNuCpos*, which predicts the effect of genetic

alterations on nucleosome positioning.

Xi et al. proposed the HBA score as the log likelihood ratio of the

probability for a given 147-bp sequence to be a nucleosome versus a linker [28].

According to their definition, the HBA score for the 147-bp region x centering at

position i (a_i) on a given genomic sequence is,

$a_i := log \left[\frac{P_N(x_{i-73},...,x_{i+73})}{G_L(x_{i-73},...,x_{i+73}|147)} \right]$,

where P_N and G_L represent the probability of observing the 147-bp sequence as

a nucleosome or a linker, respectively [28]. The probability of being a

nucleosome is calculated by referring to the parameters *freqN4* and *tranN4*,

which are derived from nucleosomal DNA sequences. Similarly, calculation of

the probability of being a linker is based on linker DNA sequences. As

nucleosomal and linker sequences do not overlap in terms of their genomic

coordinates, negativity of HBA does not directly mean that the tested sequence

is inappropriate for nucleosome formation. The *predNuCpos* function calculates

chemical map–based HBA scores along the input sequence and outputs them

as raw values as its default behavior. We developed an independent function

designated *HBA*, which only calculates the HBA score for a given 147-bp

sequence. The *HBA* function uses the abovementioned chemical parameters for

predNuCpos: *freqL*, *tranL*, *tranL2*, *tranL3*, *tranL4*, *freqN4*, and *tranN4*.

We defined 13 overlapping nucleosomal subsegments, A through M,

and developed a function designated *localHBA* that calculates "local" HBA

scores for each segment. Segment A corresponds to nucleosomal nucleotide

positions 1-21; B, 12-31; C, 22-42; D, 33-52; E, 43-63; F, 54-73; G, 64-84; H,

75-94; I, 85-105; J, 96-115; K, 106-126; L, 117-136; and M, 127-147. Similar to

the calculation of HBA [28], the local HBA score for segment A of the 147-bp

potential nucleosomal region x centering at position i (l_i) on a given genomic

sequence is calculated as,

$$l_i := log\left[\frac{P_N(x_{i-73},...,x_{i-53})}{G_L(x_{i-73},...,x_{i-53}|21)}\right],$$

where P_N and G_L represent the probability of observing the 21-bp sequence as

segment A of a nucleosome or a linker, respectively. Local HBA scores for the

other segments are calculated in the same way, except that the considered

nucleotide positions are set appropriately. At the implementation level, four-base

frequency values for the first four nucleotide positions of each segment were

prepared: *freqN4SA* corresponds to nucleosome positions 1-4; *freqN4SB*,

12-15; *freqN4SC*, 22-25; *freqN4SD*, 33-36; *freqN4SE*, 43-46; *freqN4SF*, 54-57;

freqN4SG, 64-67; *freqN4SH*, 75-78, *freqN4SI*, 85-88; *freqN4SJ*, 96-99;

freqN4SK, 106-109; *freqN4SL*, 117-120; and *freqN4SM*, 127-130. These

four-base frequency values were used to calculate the probability of the segment

as that part of nucleosomal DNA as done for HBA calculations [28]. The

parameter *freqN4SA* was identical to *freqN4*, which was used for HBA

calculations.

Prediction of nucleosome positioning with nuCpos and NuPoP and

evaluation of the prediction results

The codes for prediction, evaluation, and figure drawing used in this study are

available online (**https://doi.org/10.5281/zenodo.3523573**). Unmasked

reference genomes for the budding yeast, fission yeast, and house mouse (*Mus*

musculus) were used as prediction target sequences. For the mouse

experiments, only the 19th chromosome (Chr19) was used for prediction

because its length (61,342,430 bp) was sufficient for evaluation, at

approximately five-times longer than the total length of yeast chromosomes

(budding yeast, 12,071,326 bp; fission yeast, 12,571,820 bp). Mouse Chr19

contained 249,210 unique and 19,965,481 redundant nucleosomes that had

been determined based on histone H4 S47C-dependent cleavage [26]. The

density of redundant nucleosomes on mouse Chr19 was one per 3.07 bp. With

this density, one in three randomly located nucleosomes in the chromosome

could be counted as a truly predicted nucleosome. Thus, we selected 2,044,747

nucleosomes with the highest NCP scores as true redundant nucleosomes for

the matching experiment. This selection yielded a density of one nucleosome

per 30.0 bp, which was comparable to that of budding yeast and fission yeast

(one nucleosome per 35.0 bp and 29.5 bp, respectively).

961   The *predNuPoP* function of NuPoP and the *predNuCpos* function of

nuCpos were used for dHMM-based predictions. In order to predict using

budding yeast models, the species arguments were set as "7" for *predNuPoP*

and "sc" for *predNuCpos*. Similarly, fission yeast ("9" and "sp") and mouse ("2"

and "mm") models were specified. We defined any nucleosomes with P-values

greater than zero ($P>0$) as predicted nucleosomes. Matching of predicted

nucleosomes using *in vivo* chemical nucleosomes was done by widening the

genomic coordinates of *in vivo* nucleosomes to both sides in a step-wise manner

from zero to nine base pairs. For instance, at 1-bp resolution, a predicted

nucleosome was regarded as "matched" when the genomic coordinate of its

dyad was equal to that of the nearest *in vivo* nucleosome. If the dyad of the

predicted nucleosome was 1 bp away from that of the nearest *in vivo*

nucleosome, it was regarded as "not matched." At 2-bp resolution, a predicted

nucleosome was regarded as "matched" when the distance from its dyad to that

of the nearest *in vivo* nucleosome was <2 bp. For drawing ROC curves and

calculation of AUC, a matrix of two columns was generated for each prediction

result. In the first column, P-values of nucleosomes that were $P>0$ were stored.

In the second column, the matching status for each nucleosome according to the

matching experiments at 1-bp resolution was stored. After processing using the

prediction function of the ROCR package

(https://cran.r-project.org/package=ROCR, ver. 1.0-7), ROC curves were drawn

using the *plot* function of R. The AUC was calculated using the *performance*
function of ROCR. The matching rate of the nucleosomes on the Viterbi paths,
which were predicted by *predNuPoP* and *predNuCpos*, was calculated using
in-house scripts and plotted using the *barplot* function of R.
986    Dinucleotide frequencies for nucleosomal DNA and unmasked genomic
DNA were calculated using the *oligonucleotideFrequency* function of Biostrings.
For normalization of dinucleotide frequencies, the nucleosomal frequency was
divided by the genomic frequency. Heatmaps of 16 dinucleotide frequencies
along the nucleosome were drawn using the *levelplot* function of the rasterVis
package (https://cran.r-project.org/package=rasterVis, ver. 0.46). The *plot*
function was used for plotting the frequencies of CG and other SS dinucleotides.

993    Chemical map–based HBA scores were calculated using the

predNuCpos function or the *HBA* function of nuCpos, which yield the same
scores. The species argument was set as "sc" for budding yeast sequences and
sequences of *in vitro* reconstitution studies; for the fission yeast sequences, "sp."
Non-smoothed MNase-seq–based HBA scores were calculated using in-house
functions that utilize the parameters for the *predNuPoP* function of NuPoP. For
comparison of *in vivo* nucleosomes, 5,542 sets of −1 and +1 nucleosomes
determined by Chereji et al. [27] were used for HBA calculations. The 347-bp
sequences around these nucleosomes (from −173 to +173 nucleotide positions
with respect to the dyads) were extracted from the budding yeast genome. The
HBA score was calculated for each possible 147-bp segment along the
sequences. A/T-frequency was calculated using the *letterFrequency* function of
Biostrings for each 147-bp sequence. HBA and A/T-frequency scores were
averaged at each coordinate with respect to the −1 or +1 nucleosomes.

Chemical map–based local HBA scores were calculated using the *localHBA*

function of nuCpos. Heatmaps of local HBA scores were drawn using the
levelplot function of rasterVis.
1010
List of abbreviations:
AUC: area under the curve

CG: cytosine-guanine dinucleotide

dHMM: duration hidden Markov model

HBA: histone binding affinity

LTR: long terminal repeat

MMTV: mouse mammary tumor virus

MNase: *Micrococcus* nuclease

NCP: nucleosome core particle

NDR: nucleosome depleted region

ROC: receiver operating characteristic

SELEX: Systematic Evolution of Ligands by EXponential enrichment

SHL: superhelical location

1024

1025   **Declarations:**

1026   **Ethics approval and consent to participate:**

1027   Not applicable.

1028

1029   **Consent for publication:**

1030   Not applicable.

1031

1032   **Availability of data and materials:**

1033   The datasets generated and analyzed during the current study are available

1034   online (see **Methods** for the URLs).

1035

1036   **Competing interests:**

1037   The authors declare that they have no competing interests.

1038

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1042

1043   **Authors' contributions:**

1044   H.K. designed the study, created the software, performed the experiments, and

1045   was a major contributor in writing the manuscript. T.U. and M.S. were involved in

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1048

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1054

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Figure legends:

Figure 1. Comparison of prediction accuracy between chemical

map–based and MNase-seq-based models for yeasts. (**A**) ROC curves of

prediction results with matched-species models (upper panels) and

cross-species models (lower panels). Orange lines represent lines of slope 1

and y-intercept 0. The species of genomic sequences used for prediction

(Target) and the species used for model construction (Model) are indicated. "Sc"

stands for *S. cerevisiae*, whereas "Sp" stands for *S. pombe*. Chemical

map–based (nuCpos) and MNase-seq–based (NuPoP) models were used for

predictions. Prediction performance for representative (Unique) and redundant

(Redundant) nucleosomes are presented. Matching window was set to 0 bp. (**B**)

Distance between predicted nucleosomes and nearest *in vivo* nucleosomes.

Probabilities of Viterbi nucleosomes located at a particular distance from the

nearest *in vivo* redundant nucleosomes are plotted. Species of the target

genome and for model construction were both *S. cerevisiae* (matched-species

models). Magnified view is presented inside each plot. Arrows point to the

probability of predicted nucleosomes that are 1-bp apart from *in vivo*

nucleosomes. (**C**) Matching of nucleosomes on the Viterbi paths with *in vivo*

unique and redundant nucleosomes. Note that the redundant nucleosome

datasets contain both unique nucleosomes, which are representative (colored

red in the bar graphs), and non-representative nucleosomes (orange).

1302

Figure 2. HBA scores along *in vitro* nucleosome-forming sequences. (**A-C**)
HBA scores along nucleosome-forming sequences were calculated using
chemical map–based and MNase-seq–based budding yeast models.
Sequences analyzed were the 282-bp original Widom sequence (**A**), the 3'-LTR
of MMTV (**B**), and the *Xenopus borealis* 5S rDNA dinucleosome-forming
sequence (**C**). The scores were normalized by subtracting the mean value from
the raw value on a per sequence basis. The HBA score for a given 147-bp
nucleosome sequence was assigned to its dyad position. Orange vertical lines
indicate the dyad positions of *in vitro* reconstituted nucleosomes: nucleotide
positions 154 (**A**), 139 and 335 (**B**), and 106 and 303 (**C**). Asterisks indicate
high-scoring HBA positions around the *in vitro* positioning sites. Note that for the
5S rDNA sequence, two identical sequences are joined at position 230, causing
a difference in HBA scores around the left sides of the two *in vitro* nucleosome
positions.
1317
Figure 3. Comparison between chemical map–based and
MNase-seq–based models on selected *in vivo* regions. (**A and B**) Chemical
map–based and MNase-seq–based HBA scores (**A**) and A/T nucleotide
frequency (**B**) along the sequences containing budding yeast –1 and +1
nucleosomes for protein-coding genes. Gray vertical lines indicate the dyad
positions of respective nucleosomes. Asterisks indicate positions with relatively
high HBA scores. NDR: nucleosome-depleted region. (**C**) Prediction results for
the budding yeast *TRP1ARS1* mini-chromosome. Schematic representation of *in*
vivo nucleosome positioning is shown above the plots. Nucleosomes labeled I
through VII are indicated as ovals. Note that this sequence is circularized *in vivo*
by being linked at the *Eco*RI sites. The top two panels show the prediction
results output by nuCpos, whereas the next two panels show NuPoP results.
The upper panel in each set shows predicted occupancy of the nucleosome
(Occup., gray polygons) and probabilities of the tested 147-bp sequences for
being in the nucleosome state (P-dyad, blue vertical lines). The lower panels
show HBA values for the tested 147-bp sequences calculated using the
indicated models. The very bottom panel shows the A/T-frequencies for the
tested 147-bp sequences. Horizontal lines at the bottom of each plot indicate a

unit of the circular *TRP1ARS1* mini-chromosome (colored in gray, nucleotide

positions 0 to 1,464), the coding region of *TRP1* (red, 115-879), and the *B3*

(black, 763-788), *B2* (purple, 810-820), *B1* (green, 847-859), and *ACS* (blue,

869-879) elements of *ARS1*. Inverted triangles indicate the histone H4

S47C-dependent cleavage centers determined by indirect end-labeling; orange

for mini-chromosome and light blue for genomic experiments [36].

1342

Figure 4. Predicting the effects of repeat insertion on nucleosome

positioning. Chemical map–based HBA scores and predicted nucleosomal

occupancy were calculated for original and modified *BAR1* promoter sequences.

The sequences were centered at the dyad position of the repressive

nucleosome, in which the indicated repeat sequences were inserted. Horizontal

lines at the bottom of each plot indicate the *α2*-operator (purple), the *TATA*

(blue) element, the coding region of *BAR1* (orange), and the insert (red). Note:

the sequence insertion caused a shift of the left of the three predicted

nucleosomes to the right to cover the *α2*-operator in the occupancy plots.

Overconfidence should not be placed in this shift, as it may simply reflect that the

dHMM tends to follow the linker length distribution, which generally does not

allow longer linkers.

1355

Figure 5. Local HBA analysis of the Widom 601 sequence. (**A**) Chemical

map–based local HBA scores along the 282-bp Widom 601 sequence. The

scores for each tested 147-bp sequence were heatmapped at the center position

of that sequence. The heatmap scale indicates the local HBA score. Black

arrows indicate high-HBA-score positions (124, 135, 143, 164, and 175). Red

arrow indicates the dyad position of the *in vitro* reconstituted nucleosome (154).

The region evaluated in (**B**) is indicated as a horizontal gray bar under the X-axis.

(**B**) Local HBA scores at (red) and around (black) the *in vitro* translational

position for each segment are plotted in columns. The scores for the M segment

are magnified to the left to show the indices on the X-axis. The relative positions

−4, 0, and +4 correspond to nucleotide positions 150, 154, and 158 of the

282-bp sequence. The location of the R3 element is indicated at the top. (**C**)

Schematic representation of shifting of translational positions in (**B**). Nucleotide

positions relative to the dyad of the central translated position (i=154) are

indicated. Only three (−4, 0, and +4) of the nine positions evaluated in (**B**) are

shown.

1372

Figure 6. Local HBA analysis of modified nucleosome-forming sequences.

(**A**) Chemical map–based local HBA scores along the original and modified

fission yeast *ura4*$^+$ gene. The scores for each tested 147-bp sequence were

heatmapped at the center position of that sequence. The heatmap scale

indicates the local HBA score. Black arrows indicate the nucleosome centers

(nucleotide positions +17, +164, +332, +470, +629, and +806) determined by

MNase-seq [55]. (**B**) Chemical map–based HBA and local HBA scores for +1 to

+3 nucleosomes of the *ura4*$^+$ gene. Relative dyad positions with respect to the *in*

vivo positions are indicated for HBA plots. Local HBA scores for the *in vivo*

positions are shown. Asterisks indicate substantially affected segments.

1383

Figure 7. Comparison of prediction accuracy between chemical

map–based and MNase-seq–based models for mice. (**A**) Normalized

frequencies of dinucleotides starting at indicated nucleosomal positions. The

heatmap scale indicates the normalized dinucleotide frequency. (**B**) Normalized

CG frequency across the nucleosome. Triangles, stars, and horizontal bars

indicate positions and regions with mouse-specific characteristics. Gray vertical

lines indicate the positions of dyad (solid) and histone-DNA contact sites (SHL

±0.5-6.5). (**C**) ROC curves of prediction results with matched-species models.

"Mm" stands for *M. musculus*. Prediction performance for representative

(Unique) and redundant (Redundant) nucleosomes are presented. (**D**) Matching

of nucleosomes on the Viterbi paths with *in vivo* unique and redundant

nucleosomes.

1396

Supplementary Figure Legends:

Additional file 1: Figure S1. Linker length distributions utilized in the

construction of chemical map–based and MNase-seq–based models. The

linker length distributions of three species implemented in each package are

plotted. A magnified view ranging from 0 to 100 bp in linker length is presented

inside each plot.

1403

1404   **Additional file 1: Table S1. Area under the curve scores for the prediction**

1405   **results shown in Figure 1A.**

1406

Additional file 1: Figure S2. Matching rate between predicted and *in vivo*

nucleosomes with variable matching windows. The species of genomic

sequences used for prediction (Target) and the species used for model

construction (Model) are indicated. "Sc" stands for *S. cerevisiae*, whereas "Sp"

stands for *S. pombe*. Chemical map–based (nuCpos) and MNase-seq–based

(NuPoP) models were used for predictions. Matching rates for representative

(Unique) and redundant (Redundant) nucleosomes are presented.

1414

1415   **Additional file 1: Figure S3. Magnified view of prediction results for**

1416   ***TRP1ARS1.*** Prediction results for the budding yeast *TRP1ARS1*

1417   mini-chromosome output by nuCpos and NuPoP (**Figure 3C**) were magnified,

1418   being centered at nucleosome II.

1419

Additional file 1: Figure S4. Prediction results for the fission yeast *ura4*$^+$

gene. Schematic representation of *in vivo* nucleosome positioning is shown

above the plots. Nucleosomes numbered +1 to +6 are indicated as ovals. The

top two panels show the prediction results output by nuCpos, whereas the next

two panels show NuPoP results. The upper panel in each set shows predicted

occupancy of nucleosomes (Occup., gray polygons) and probability that the

tested 147-bp sequences are in the nucleosome state (P-dyad, blue vertical

lines). Lower panels show HBA values for the tested 147-bp sequences

calculated using the indicated models. The very bottom panel shows the

A/T-frequency for the tested 147-bp sequences. Horizontal lines at the bottom of

each plot indicate the 5'- and 3'-untranslated regions (colored in gray, nucleotide

positions –151 to –1 and +795 to +986, respectively) and the protein-coding

region (red, 0 to +794) of the *ura4*$^+$ gene. Inverted triangles indicate the

nucleosome centers determined by MNase-seq [55].

1434

Additional file 1: Figure S5. Prediction of the effects of repeat insertion in the fourth nucleosome of the *TALS* minichromosome. Chemical map–based HBA scores and predicted nucleosomal occupancy were calculated for original and modified *TALS* sequences [56]. The sequences were centered at the dyad position of the fourth nucleosome (0 bp), in which the indicated repeat sequences were inserted. Note: the position for the fourth nucleosome was predicted to shift to the right. Horizontal lines at the bottom of each plot indicate the $\alpha2$-operator (purple) and the insert (red). hTEL stands for human telomeric repeat (5'-TTAGGG-3'); SI-A, sequence isomer-A (5'-TGTAGG-3'); SI-B, sequence isomer-B (5'-TGTGAG-3').

1445

Additional file 1: Figure S6. Thirteen overlapping nucleosomal DNA subsegments for local HBA calculation. Segments A through M are colored in orange on the nucleosome structure 1AOI [1]. The structures were drawn using MacPyMOL (v1.8.4.1). The base pair length (red) and corresponding superhelical locations (black) of each segment are indicated. The color of the right-half segments (H-M) is faded because they are behind the front helix.

1452

Additional file 1: Figure S7. Local HBA analysis of the *in vitro* reconstitution sequences. Local HBA scores at (red) and around (black) the *in vitro* nucleosome position for each segment are plotted in columns. Due to the lack of flanking sequences, shifting the translational position to the left and right sides inhibits local HBA calculations for terminal segments. Names of reconstituted nucleosomes are indicated to the left. Note that the 601LR sequence is not completely identical to the original 147-bp sequence centering at nucleotide position 154 (**Figure 5B**). The sequences of 601LR, 601L, and 601R differ at their termini for biochemical handling. For 601LR, the four original terminal bases (5'-CTGG-3' and 5'-CTGT-3') have been replaced with three-base sequences (5'-ATC-3' and 5'-GAT-3'; i.e., blunt ends created by *Eco*RV digestion) [12, 13]. Here, the nucleotide base A was added to both ends of the 145-bp sequence to lengthen it to 147-bp for local HBA calculations.

1466

Additional file 1: Figure S8. Dinucleotide frequency across chemical

unique nucleosomes. (**A**) Non-normalized frequencies of dinucleotides starting

at indicated nucleosome positions. The heatmap scale indicates the dinucleotide

frequency (log10). Note: AA-TT, AC-GT, AG-CT, CA-TG, CC-GG, and GA-TC

dinucleotide pairs exhibit rotational symmetry to each other, whereas AT, CG,

GC, and TA dinucleotides exhibit point symmetry by themselves. AA-TT, AC-GT,

AG-CT, and TA dinucleotides are highly enriched at SHL ±0.5. (**B**) SS

dinucleotide frequency. Gray vertical lines indicate the positions of dyad (solid)

and histone-DNA contact sites (SHL ±0.5-6.5). Mean frequency of each

dinucleotide in the unique nucleosomes is indicated to the right and shown as an

orange horizontal bar in the plot.

1478

1479 **Additional file 1: Figure S9. Matching rate analysis for the mouse model.**

1480 Matching rate between predicted and *in vivo* nucleosomes with variable

1481 matching window is shown. The sequence of mouse Chr19 was used for

1482 prediction with the mouse chemical map–based (nuCpos) and

1483 MNase-seq–based (NuPoP) models.

1484

1485

Figure 1

Figure 2

A

B

C

Figure 3

Figure 4

Figure 5

A

B

C

Figure 6

A

Figure 7

A

B

C

D