Genome-Wide Covariation in SARS-CoV-2

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Abstract

The SARS-CoV-2 virus causing the global pandemic is a coronavirus with a genome of about 30Kbase length [Song et al., 2019]. The design of vaccines and choice of therapies depends on the structure and mutational stability of encoded proteins in the open reading frames(ORFs) of this genome. In this study, we computed, using Expectation Reflection, the genome-wide covariation of the SARS-CoV-2 genome based on an alignment of ≈ 130000 SARS-CoV-2 complete genome sequences obtained from GISAID[Shu & McCauley, 2017]. We used this covariation to compute the Direct Information between pairs of positions across the whole genome, investigating potentially important relationships within the genome, both within each encoded protein and between encoded proteins. We then computed the covariation within each clade of the virus. The covariation detected recapitulates all clade determinants and each clade exhibits distinct covarying pairs.

Keywords: SARS-CoV-2, Genome, Analysis

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1 Introduction

Severe Acute Respiratory Syndrome (SARS) is a viral respiratory disease caused by the SARS-associated coronavirus. In December 2019, this pneumonia-like disease re-emerged in the Chinese city of Wuhan and the novel beta-coronavirus 2 (SARS-CoV-2) was identified as the causative agent [Zhu et al., 2020]. The genome was first characterized by Wu et al. in December 2019 [Wu et al., 2020]. Since then the SARS-CoV-2 virus has spread relentlessly all over the world and been declared a worldwide pandemic with 79 million cases leading to 1.7 million deaths to date [World Health Organization, 2020, John Hopkins University, 2020]. SARS-CoV-2 is an +ssRNA virus belonging to the coronavirus family major genera Betacoronavirus [Gorbalenya et al., 2020]. The viral genome encodes several open reading frames (ORFs): ORF1ab, ORF3a, ORF6, ORF7a, ORF7b, ORF8, ORF10. These ORFs encode for several non-structural proteins (NSPs) while there are specific regions encoding the spike glycoprotein (S), envelope (E), membrane glycoprotein (M), and the nucleocapsid protein (N). The genome (NC_045512.2, 29870 nucleotides long) of the virus can be broken into 11 encoding regions: ORF1ab (266-21555), S (21563-25384), ORF3a (25393- 26220), E (26245-26472), M (26523-27191), ORF6 (27202-27387), ORF7a (27394-27759), ORF7b (27756-27887), ORF8 (27894-28259), N (8274-29533), ORF10 (29558-29674) [NCBI, 2020].

While the reference genome is used for most investigations, there is also an abundance of data available which can be used to monitor variations in the genome and analyse the the evolution and nature of the virus. This data was assembled by GISAID to document different strains of the virus in a new database: EpiCoV. With the first viral entry on January 10 2020, the database has grown to 292,000 submissions [Shu & McCauley, 2017]. In this study we use 137636 of these strains to analyse the evolution of the virus.

In our analysis we develop a co-evolutionary interaction network of nucleotide positions using an entropy-based method to infer genome-level interaction in the SARS-CoV-2 genome.

1.1 Coevolution

The variation of the virus's genetic structure is of considerable medical and biological importance for prevention, diagnosis, and therapy. Mutations in the viral genome allows us to investigate potentially important relationships within the genome. Comparative RNA sequence sequence analysis has long been used to investigate co-evolution via covariance of nucleotide mutations (30,31) with difficulty arising in the separating of indirect and direct interactions that lead to such co-variation. A similar issue in inferring protein residue interactions was addressed by Direct Coupling Analysis (DCA) which successfully inferred direct interactions (DIs) in proteins as well as between proteins [Weigt et al., 2009]. Recently DCA was also applied to RNAs and RNA-protein complexes [De Leonardis et al., 2015] For RNAs, the DCA-based methods infer physical interactions, both secondary and tertiary,

between nucleotides in an RNA molecule by analyzing the co-evolutionary signals of nucleotides across sequences in the RNA family [De Leonardis et al., 2015]. In this paper we will utilize Expectation Reflection [Hoang et al., 2019a, Hoang et al., 2019b] with DCA to infer DI in the SARS-CoV-2 genome. These interactions may also provide information on protein-protein interaction. Additionally this analysis could be useful in vaccine development, aiding in efforts to mitigate "escape pathways" for the virus to use in future strains [Dahirel et al., 2011].

1.2 SARS-CoV-2 Genome Analysis using Expectation Reflection

Our analysis begins with the acquisition and alignment of genome sequence data, described in Section 4.2. Once the data is aligned we pre-process the aligned sequences by removing sequence positions which contain 95% or more conservation as discussed in Section 2.1. We infer covarying positions from the curated-aligned genome data using DCA-ER which is outlined in Section 4.1. The resulting genome-wide interactions are discussed by encoding region in Section 2.2. Our analysis includes the presentation of position interaction maps and tabulation of the strongest resulting DI pairs. For the strongest DI pairs we also present the single site amino acid (AA) frequency as well as the AA-pair counts. Similar analysis is also applied to the G, GR, GH, S and V clades in Section 2.3.

2 Results

2.1 Clade Incidence

As in any ab initio inference problem, when inferring co-evolutionary interactions between nucleotide positions in the SARS CoV-2 genome, we must consider certain properties of the data at hand. As an example, the length of the full genome is approximately 29000 nucleotide positions. However, when we consider genome positions in which no single nucleotide is expressed more than 95% of the time (95% conserved), the relevant positions are reduced by approximately two-thirds. Decreasing the conserved percentage decreases the number of allowed repetitions in a given position (data column). In other words, as we decrease the threshold for conserved columns, the condition for variation at a given position becomes more stringent and the number of columns retained for analysis will decrease. As in the example above, going from 100% (full genome, all columns allowed) to 95% conservation removes a significant number of genome positions. Because inference with ER relies on mutations at a given position we must consider the resulting number of columns, or incidence, after such curation. In addition, region-specific incidence may also underline importance to the efficacy of the virus because higher incidence represents more variation and mutation. We also consider the clade-specific incidence of the full genome since we will consider genome interactions in different clades in future sections.

In Figure 1 we plot the incidence of the ORF1ab and S regions for different thresholds of allowed conservation. These incidence curves are given for the different clade data sets. Figure 1 shows that region incidence varies between clades and that the incidence of different encoding regions is affected differently for a given clade. For example, consider the full genome data set against the S clade set in Figure 1. The full genome data set (blue) has one of the highest ORF1ab incidence curves, but the same level of incidence is not necessarily expressed in the S region. In contrast, the S clade (purple) shows middling incidence for ORF1ab and one of the strongest incidence curves for the S encoding region.

This analysis can also give some intuition on the nature of individual encoding regions by quantifying the level of variability expressed within a given clade. For example, in Figure 1, we see differences in which clades express higher incidence between the ORF1ab and S encoding regions. We can apply the same principle to compare the ORF1ab and S regions in the full genome data set. In Figure 2, we plot the incidence of ORF1ab and S in the full genome sequence set as we increase the allowed conserved percentage per given nucleotide position. This figure shows different levels of position-wise variability for the two encoding regions.

For the remainder of the paper we will set the conservation threshold to 95%. This is in order to retain a significant number of positions for the subsequent analysis. We must also consider that the size of a given clade, or genome data set will affect the incidence and variability. Specifically, as the number of sequence considered changes, the level of variability, enforced by the conservation thresholds, will be altered as well. Therefore,

FIGURE 1: **Comparing Incidence across Clades.** We plot total number of retained columns (incidence) against the allowed conserved percentage per a given nucleotide position for both ORF1ab and S regions (across all clades).

FIGURE 2: **Comparing the Incidence of S and ORF1ab.** We plot the percentage of retained columns (incidence) against the allowed conserved percentage per a given nucleotide position (in the full genome data set).

112 when considering smaller data sets, such as the S and V clades, we must keep in mind that
 113 the incidence is affected by the cardinality of the set itself.

2.2 Genome Wide Analysis

We begin by inferring interactions between nucleotide positions across the entire genome. Figure 3 shows a gray-scale of DI calculated from inferred couplings between positions (i, j) using all available sequences. Position pairs which showed significant coevolution ($DI \geq .1$) are emphasized. In Figure 3, the full interaction map is dominated by interactions in ORF1ab (positions 266-21556), S (positions 21564-25384), and ORF7ab (27395-27888). Proximal nucleotide positions (diagonal of the interaction map) express strong covariation as shown by the thick black diagonal bar. In fact, we suppress the emphasis of $DI > 0.1$ for proximal pairs ($\|i - j\| < 10$) in all interaction maps due to the prevalence of proximal pair interactions with $DI > 0.1$. However, there are several off-diagonal position pairs (far apart in the genome) which show strong covariation. This shows potential evolutionary links between specific positions or regions in different parts of the genome. As an example we can consider the top 5 DI pairs for the entire genome in Table 2.2. While most of the position pairs are proximal, the strongest interaction is more than 20000 nucleotides apart.

Position 1	Position 2	DI
2237	22384	0.915
28881	28883	0.801
29700	29721	0.670
241	313	0.665
14408	3037	0.456

In order to further explore features from the full interaction map we will divide the full genome into different encoding regions, focusing on those regions which show significant incidence.

2.2.1 ORF1ab

The ORF1ab region of SARS-CoV-2 genome is an important polyprotein gene which encodes 16 nonstructural proteins important to the life cycle of the virus. Because of this importance, some of the proteins encoded in this region have been proposed as potential targets for antiviral therapy [Kwong et al., 2005, Briguglio et al., 2011, Zhou et al., 2020]. Figure 3 shows that the region also has the largest number of non-conserved nucleotide positions, or position incidence, (as described in Section 2.1) of the major encoding regions. This increased incidence is expressed in the cardinality of the interaction map.

Table 1 shows the top 10 DI pairs in ORF1ab with bolded positions representing distal (non ORF1ab) positions. Note that more than half of the top 10 DI pairs in Table 1 are distal which may be an indicator of the significance of the region to other encoding regions (and their resulting functions).

FIGURE 3: **hCoV-19 Genome-Wide Interaction Map.** We infer covariation in nucleotide positions across ≥ 130000 sequences.

While the interaction map and DI pairs are a useful overview of genome coevolution, it is important to consider whether these coevolving positions result in alterations of amino acids encoded by the interacting positions. Table 2 gives the resulting proportion of amino acids (AA) encoded by the nucleotide positions outlined in Table 1. The table shows frequent occurrence for a dominant AA at any given position. This analysis can be extended to consider the AA pair counts for a given genome position pair. Table 3 shows the AA pair counts of the dominant DI pairs in ORF1ab. In the given position pair matrices we see three cases arise: A high AA-pair count on the diagonal, on a single row/column, or in a single element. A high AA-pair count on the diagonal means the prevalence of two AA-pairings resulting from the coevolution of the two positions. The AA-count between positions 14408 and 23404 is a good example of this first case. Dominance of a given row or column suggests that one position remains mostly fixed while the other position expresses variability, as seen in the AA-counts for the position position pairing of 3037 and 23403 where 3037 almost always encodes Phenylalanine. The final case in Table 3 is a single AA-pair expressed dominantly for a given position as seen with positions 21367 and

FIGURE 4: **ORF1ab Interaction Map.**

Position 1	Position 2	DI
14408	3037	0.456
1059	25563	0.441
14805	26144	0.380
7540	23401	0.343
14408	23404	0.340
3037	23403	0.335
21254	22227	0.329
18555	23401	0.313
21367	21369	0.291
1163	23401	0.283

TABLE 1: **Top 10 ORF1ab DI pairs.** Listing the strongest DI pair positions (bolded positions not in ORF1ab)

	Single Site Freqs.
14408	L: .857, P: .139
3037	F: .995
1059	T: .832, I: .164
25563	Q: .783, H: .215
14805	Y: .998
26144	G: .945, V: .040
7540	T: .997
23401	Q: .999
23404	G: .861, D: .138
23403	G: .861, D: .138
21254	A: .933, X: .106
22227	A: .956, V: .029
18555	D: .999
21367	I: .941, X: .059
21369	I: .941, X: .059
1163	I: .938, F: .059

TABLE 2: ORF1ab Single Site AA Frequencies. We consider the distributions of resulting amino acids from the nucleotide positions which had the highest DI in ORF1ab

21369. This case shows little coevolution and generally occurs in AA-pairs from positions with lower DI where both positions have a dominant AA in their single site AA frequency (see 21367 and 21369 in Table 2). We continue with the same analysis for the S encoding region.

2.2.2 Spike Glycoprotein

The Spike protein encoding region (S) plays a vital role in viral entry into the host cells [Gallagher & Buchmeier, 2001]. As a result this region is considered a key target in current vaccine development [Tai et al., 2020]. In Figure 5 and Table 4 we present both the interaction map and the top ranked DI pairings respectively for the S region gene positions. In addition to this DI analysis we present the single site frequencies and AA-pair non-singular AA-counts in Tables 5 and 6. For the S encoding region we only include the top 3 rated DI amino acid pairings. Regardless of this curation, the AA-pair matrices in Table 6 show a single AA-pair count prevalence for all but the strongest DI pairing. This pairing, between positions 22363 and 22384, shows a strong diagonal. However, the alternate can be any amino acid pairing which shows that the main trend is the threonine-valine combination.

3037 14408	F	other	14408 23404	L	P	other	1059 25563	T	I	other
L	117404	497	G	117540	457	521	Q	107023	257	434
P	19006	117	D	269	18615	72	H	7274	22237	99
other	544	68	other	101	40	21	other	223	45	44
3037 23403	F	other	21254 22227	A	X	other	14805 26144	Y	other	
G	117983	535	A	123066	8487	14	G	129808	259	
D	18827	129	V	3845	246	0	V	5532	12	
other	143	19	other	1452	525	1	other	1988	37	
21367 21369	I	X	other	1163 23401	I	F	other			
I	129512	0	0	Q	128884	8055	488			
X	0	8112	0	other	172	23	14			
other	0	0	12							

TABLE 3: **ORF1ab AA Pair Counts.** Encoded amino acid counts for high ranked DI positions in ORF1ab. Considering the most prevalent amino acids for each position.

Position 1	Position 2	DI
22363	22384	0.915
23401	7540	0.343
23401	18555	0.313
22497	22495	0.301
22353	22355	0.292
23401	1163	0.283
23401	16647	0.275
22334	22336	0.263
22539	22541	0.245
22526	22524	0.239

TABLE 4: **Top 10 S DI pairs.** Listing the strongest DI pair positions (bolded positions not in S)

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177 2.2.3 ORF3a

178 The ORF3a gene region encodes a unique membrane protein with a 3-membrane structure
179 and it is essential for the pathogenesis of the disease [Lu et al., 2010, Issa et al., 2020].

FIGURE 5: **S Interaction Map.**

180 The interaction map of ORF3a expresses minimal incidence so it is not shown. However,
 181 the interactions in ORF3a are still important to consider. The region itself shows little
 182 variation (only 5 pairs have $DI > 0.1$) with the exception of position 25563 as seen in
 183 previous work [Uğurel et al., 2020]. Regardless, in Table 7 we are able to show that 25563
 184 interacts with several other regions including ORF1ab and S with the strongest coevolution
 185 occurring with position 1059 in the ORF1ab region. We consider the encoded amino acids
 186 for positions coevolving in ORF3a in Tables 8 and 9. In Table 9 we see a new case in the
 187 AA-pair distribution with position pairs of 25563 and both 22992 and 25429. In both these
 188 pairs, the majority of the AA pair count is the primary AA for each position. However,
 189 the second most prevalent pairing is in the primary-secondary AA couples for the position.
 190 While a high count on the matrix diagonal represents the prevalence of two AA pairs, the
 191 distribution in these pairs shows more variety with 3 significant pairings expressed in the
 192 position interaction.

	Single Site Freqs.
22363	V:.894,X:.106
22384	T:.896,X:.104
23401	Q:.998,X:.001
7540	T:.997,X:.003
18555	D:.997,X:.003
22497	I:.893,X:.107
22495	G:.893,X:.107
22353	A:.891,X:.109
22355	
1163	I:.938,X:.057
16647	T:.989,X:.011
22334	W:.937,X:.062
22336	W:.938,X:.062
22539	I:.951,X:.049
22541	V:.994,X:.005
22526	P:.947,X:.053
22524	Q:.937,X:.062
22354	A:.891,X:.109
22488	E:.893,X:.106

TABLE 5: **S Single Site AA Frequencies.** We consider the distributions of resulting amino acids from the nucleotide positions which had the highest DI in S

22363	T	X	other	23401	Q	X	other	23401	Q	X	other
22384				7540				18555			
V	122556	426	13	T	137009	115	69	D	137074	91	68
X	736	13882	1	X	417	25	0	X	353	49	1
other	8	1	13	other	1	0	0	other	0	0	0

TABLE 6: **S AA Pair Counts.** Encoded amino acid counts for high ranked DI positions in S. Considering the most prevalent amino acids for each position.

2.2.4 ORF7ab

ORF7ab contains a viral antagonist of host restriction factor BST-2/Tetherin and induces apoptosis [Holland et al., 2020]. We present the interaction map for both ORF7a and ORF7b separately in Figures 6 and 7. We also present the top 10 DI pairs for each region in Table 10.

Position 1	Position 2	DI
25563	1059	0.441
25563	22444	0.202
25563	22992	0.155
25563	25429	0.129
25563	20268	0.117

TABLE 7: **Top 5 ORF3a DI pairs.** Listing the strongest DI pair positions (bolded positions not in ORF3a)

	Single Site Freqs.
25563	Q:.783,H:.215
1059	T:.832,I:.164
22444	D:.891,X:.109
22992	S:.914,N:.046,X:.039
25429	V:.893,L:.105
20268	L:.961,X:.039

TABLE 8: **ORF3a Single Site Amino Acid Frequencies.** We consider the distributions of resulting amino acids from the nucleotide positions which had the highest DI in ORF3a

199 It is important to note that there was little significant coevolution between positions in
200 ORF7ab and other regions of the genome. We will only present the AA single site fre-
201 quencies, in Table 11 for this region because of the single AA dominance at each position
202 considered. In addition to this strong dominance ($\geq 90\%$) of the primary AA at each
203 position, the secondary AA at all positions was undefined (X).

204 2.2.5 Nucleocapsid

205 We conclude our complete genome analysis with a brief description of our findings of
206 coevolution in the Nucleocapsid (N) encoding region. The N protein plays varied roles in
207 the regulation of the infected cell metabolism and packaging of the viral genome. Therefore,
208 the protein plays an important role in both replication and transcription [Kang et al., 2020].
209 The N region contains an specific nucleotide variation in the triplet 28881, 28882, and
210 28883 discussed in previous work [Uğurel et al., 2020]. This triplet, appropriately, presents
211 the only $DI \geq 0.1$ in the region, as presented in Table 12.

25563 1059	Q	H	other	25563 22444	Q	H	other	25563 22992	Q	H	other
T	107027	7275	222	D	95971	26464	226	S	97416	28147	226
I	254	22236	45	X	11721	3134	84	N	5870	507	4
other	434	99	44	other	22	12	2	other	4429	956	81

25563 25429	Q	H	other	25563 20268	Q	H	other
V	93248	29530	124	L	103696	28365	251
L	14391	20	2	X	4013	1245	59
other	76	60	185	other	6	0	1

TABLE 9: **ORF3a AA Pair Counts.** Encoded amino acid counts for high ranked DI positions in ORF3a. Considering the most prevalent amino acids for each position.

FIGURE 6: **ORF7a Interaction Map.**

FIGURE 7: **ORF7b Interaction Map.**

Position 1	Position 2	DI
27801	27803	0.365
27688	27792	0.333
27698	27700	0.299
27579	27581	0.295
27803	27805	0.277
27794	27796	0.268
27804	27806	0.248
27805	27807	0.227
27758	27761	0.209
27688	27752	0.188

TABLE 10: **Top 10 ORF7ab DI pairs.** Listing the strongest DI pair positions

	Single Site Freqs.
27801	F:.934,X:.065
27803	F:.934,X:.065
27792	F:.929,X:.071
27688	P:.904,X:.096
27698	L:.904,X:.1
27700	I:.903,X:.1
27579	I:.902, X:.097
27581	F:.901,X:.099
27805	L:.941,X:.058
27794	F:.929,X:.071
27696	F:.931,X:.069
27804	L:.941,X:.058
27806	L:.941,X:.058
27807	L:.988,X:.011
27761	I:.902,X:.097
27752	T:.902,X:.098

TABLE 11: **Single Site Amino Acid Frequencies.** We consider the distributions of resulting amino acids from the nucleotide positions which had the highest DI in ORF7ab

Position 1	Position 2	DI
28881	28883	0.801

TABLE 12: **Nucleocapsid (N) DI pair.** The single pairing ≥ 0.1 is also one of the strongest DI in the genome.

2.3 Clades

When investigating genetic variance, it is useful to stratify available data to understand and analyse genomic diversity. Analysis of genetic variance plays a crucial role in expanding knowledge and developing prevention strategies. Previous work has developed phylogenetic trees and divided the SARS-CoV-2 genome both genomically and geographically into clades [Mercatelli & Giorgi, 2020]. We extend this analysis to see how such stratification affects the virus's genome-wide covariation. Before presenting our results on clades, it is important to note that our initial results yielded many previously defined clade determinants [Mercatelli & Giorgi, 2020]. These determinant nucleotide (NT) positions are bolded in Table 13. In the following sections we apply our method to these clades and investigate the resulting change in the coevolution of NT positions across the genome.

Clade Determinants Present in DI				
Position 1	Position 2	DI	Region	Clade
14408	3037	0.456	ORF1ab	G
1059	25563	0.441	ORF1ab	GH
14805	26144	0.380	ORF1ab	V
14408	23404	0.340	ORF1ab	G
3037	23403	0.335	ORF1ab	G, GR
25563	1059	0.441	ORF3a	G
25563	22444	0.202	ORF3a	G
25563	22992	0.155	ORF3a	G
25563	25429	0.129	ORF3a	G
25563	20268	0.117	ORF3a	G
28881	28883	0.801	N	GR

TABLE 13: **Clade Determinants in Genome-Wide Analysis.** We outline the clade determinants from DI presented in Section 2.2 (bolded)

2.3.1 G Clade

We begin our clade analysis with the largest existing clade. The G clade is stratified by the most common set of events, a quadruplet of mutations: C241T, C3037T, C14408T, A23403G [Mercatelli & Giorgi, 2020]. Extracting genome sequences with these features we re-apply ER, resulting in the interaction map in Figure 8. Comparing the full interaction map (Figure 3) and the G clade interaction map (Figure 8), we see a drastic change in incidence.

Both genome sequence sets have the same curation applied, with pre-processing removing genome positions which were $\geq 95\%$ conserved. However, within the G clade we see a severely decreased incidence in ORF1ab, with positions from NT 19300 to 19500 no longer showing sufficient variation. This change in incidence is expressed in Figure 9 as a decrease in cardinality of the interaction map from the full genome set to the G clade genome set.

The incidence change in the S encoding region is much less severe. The NT range from 2200 to 24000 appears mostly unchanged, showing the same pattern of significant DI ($DI > 0.1$, red dots). In addition to the changed incidence of ORF1ab and S. While variation of the different encoding regions differs in ORF1ab and S, there are alterations in the top ranked DI positions throughout both regions.

First consider Table 14, which gives the top ranked DI pairs in ORF1ab for the full genome sequence set and the G clade genome sequence set side by side. None of the top

FIGURE 8: **G Clade Full Genome Interaction Map.**

FIGURE 9: **ORF1ab Interaction Maps.** Showing the interaction map for the ORF1ab region with both the full genome sequence set (left), as well as the G clade genome sequence set (right)

Full Genome			G Clade		
Position 1	Position 2	DI	Position 1	Position 2	DI
14408	3037	0.456	7501	22870	0.458
1059	25563	0.441	18516	22870	0.323
14805	26144	0.380	16608	22870	0.321
7540	23401	0.343	7501	16608	0.278
14408	23404	0.340	1125	28963	0.262
3037	23403	0.335	1125	22870	0.257
21255	22227	0.329	1550	28666	0.250
18555	23401	0.313	19257	19259	0.231
21367	21369	0.291	18516	7501	0.230
1163	23401	0.283	7501	18516	0.230

TABLE 14: **ORF1ab top ranked DI pairs.** We show the 10 top ranked DI pairs for ORF1ab generated from the full genome sequence set and the G clade genome sequence set

ranked DI pairs from the full genome analysis remain in the top ranked pairs for the G clade. This is not due to an overall loss in information, as the DI magnitude remains in the same region ($DI \in [0.2, 0.4]$). Most of the removed pairs were G clade determinants, therefore these positions are fixed in the G clade, specifically positions 14408, 3037, 23403 (and proximal positions). By fixing these positions we effectively removed the variation of positions represented in 6 of the top 10 pairs. However, it seems that the connection between ORF1ab and other encoding regions, specifically the S region, was retained. Consider the NT position 23403 from the S encoding region, which was fixed in the G clade genome sequence set. During the stratification of the G clade genome sequence set, the variation at 23403 (likely 23401 and 23404 as well) was removed. This small NT group in region S accounted for 4 of the top 10 DI pairs for ORF1ab. However, while 23403 and its corresponding positions no longer coevolved with ORF1ab, the NT position 22870 expressed a very strong connection with ORF1ab in the G clade.

This trend continues in the S encoding region. Table 15 shows the top ranked DI pairs in the S encoding region for the full genome sequence set and the G clade genome sequence set. As before, none of the top ranked DI pairs from the full set survive the stratification which creates the G clade genome sequence set.

2.3.2 Other Clades

We conclude our analysis with an overview of the remaining clades presented in previous work: GR, GH, S, and V clades [Mercatelli & Giorgi, 2020]. Specifically we present the interaction maps for the different clades (Figures 10-13).

Full Genome			G Clade		
Position 1	Position 2	DI	Position 1	Position 2	DI
22363	22384	0.915	21832	21853	0.803
23401	7540	0.343	22870	7501	0.458
23401	18555	0.313	22870	18516	0.323
22497	22495	0.301	22870	16608	0.321
22353	22355	0.292	21822	21824	0.265
23401	1163	0.283	21966	21964	0.264
23401	16647	0.275	21964	21966	0.263
22334	22336	0.263	22870	1125	0.257
22539	22541	0.245	21995	21993	0.244
22526	22524	0.239	22008	22010	0.236
22354	22488	0.218	21803	21805	0.234

TABLE 15: **S top ranked DI pairs.** We show the 10 top ranked DI pairs for S generated from the full genome sequence set and the G clade genome sequence set

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269 With the given number of sequences in the smaller clades, the sample size limits the
 270 inference. This is evident when considering the shift in DI threshold in the Figures 10-13
 271 with significant DI changing $0.1 \rightarrow 0.025$. Due to the smaller sample sizes in these clades,
 272 we forego further analysis as the inference would be unreliable.

FIGURE 10: GH Clade Interaction Map. Showing the interaction map for the GH clade genome sequence set

FIGURE 11: **GR Clade Interaction Map.** Showing the interaction map for the GR clade genome sequence set

FIGURE 12: **S Clade Interaction Map.** Showing the interaction map for the S clade genome sequence set

FIGURE 13: **V Clade Interaction Map.** Showing the interaction map for the V clade genome sequence set

3 Discussion

In this work we have presented a novel analysis of the SARS CoV-2 genome by finding genome interactions both within and across encoding regions. In our analysis of the SARS CoV-2 genome we have presented several perspectives on nucleotide interactions in the genome. These interactions showed both proximal interactions within individual encoding regions as well as distal interactions between different encoding regions throughout the genome. We inferred nucleotide position interactions for the entire genome as well as the separate encoding regions. Particular attention was given to the ORF1ab and S regions, which demonstrated the highest variability in the given dataset. We were able to draw analogous conclusions from previous work by inferring the the most common variations previously reported [Uğurel et al., 2020]. Additionally, our genome-wide interaction maps expressed determinant positions of all clades available at the time our data was acquired [Mercatelli & Giorgi, 2020]. Generating interaction maps of individual clades showed clade-specific coevolution of nucleotide positions.

We further considered the level of variability, both within regions of the full genome data set and for different clades. This was accomplished by varying the threshold for conserved columns while considering the retained column incidence. This relationship shows nucleotide variability is different both between encoding regions of the full genome and between different clades. Region-specific incidences are not consistent between clades, with individual regions expressing different variability in different clades. Comparison of region-specific incidence can also give intuition on the level of variability or specific regions within specific clades.

Future extensions of this analysis provide several avenues of investigations. First, as the database of SARS CoV-2 genomes grows, the incidence and overall variability will increase, yielding further insights into genome interactions. Additionally, the availability of data over longer time periods will allow for chronological compartmentalization of genome data sets and interaction maps can be compared across the temporal evolution of the virus. Second, this analysis can also be applied to diseases for which there is more data available as the importance of genome interactions is not SARS-CoV-2 specific.

4 Materials and Methods

4.1 Expectation Reflection

To infer position pair couplings we first utilize a data-driven method, Expectation Reflection (ER), which outperforms current methods in inferring network interactions between binary variables, especially for small sample sizes[Hoang et al., 2019b]. Here we outline the method and how it is applied to infer connections between genome positions. We begin with a given genetic sequence,

$$\xi = (A, T, T, A, A, A, G, \dots, A) \quad (1)$$

In order to translate this into a binary variable sequence required for Expectation Reflection we can use a OneHot transformation [Pedregosa et al., 2011]. This transformation converts a nucleotide into a binary representation,

$$\begin{aligned} A &\longrightarrow 1000 \\ G &\longrightarrow 0100 \\ T &\longrightarrow 0010 \\ C &\longrightarrow 0001 \end{aligned}$$

which allows us to convert the genome sequence set into a binary sequence set. Therefore the previous sequence in Equation 1 becomes $\sigma = \text{OneHot}(\xi)$,

$$\sigma = (1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, \dots, 1, 0, 0, 0) \quad (2)$$

Now that we have established the conversion of a set of genetic sequences into a set of binary variables we can continue to the application of Expectation Reflection. Given a binary variable $\sigma(t)$ representing the t^{th} sequence such that with $t \in [1, N = 137686]$ sequences, or states, which the SARS-CoV-2 virus genome can take. An individual sequence has the form $\sigma = (\sigma_1, \sigma_2, \dots, \sigma_{NT})$ where NT is the number of binary variables representing the nucleotides such that with the 29903 length genome $NT = 29903 \text{ times } 4$. We can then assume that given a current sequence $\sigma(t)$, an individual position in a future sequence changes stochastically according to the following conditional probability,

$$P[\sigma_i(t+1)|\sigma(t)] = \frac{e^{\sigma_i(t)H(t)}}{\sum_{\sigma_i(t)} e^{\sigma_i(t)H(t)}} \quad (3)$$

where the local field, $H_i(t)$,

$$H_i(t) = \sum_j^N W_{ij} \sigma_j(t) \quad (4)$$

where W_{ij} represents the connection between positions i and j . H_i is a function of the current sequence state $\sigma(t)_i$ and expresses the influence of a given sequence position σ_j on the future state of sequence position σ_i . This conditional relationship allows us to iteratively search for the ideal W using all N available sequences. The method, and resulting algorithm, is discussed in further detail in previous work [Hoang et al., 2019a, Hoang et al., 2019b]

With the resulting coupling matrix we can calculate the Direct Information (DI) between all position pairs using Direct Coupling Analysis, which has been widely used to infer such interactions in previous work. [Weigt et al., 2009, Morcos et al., 2011, Ekeberg et al., 2014, De Leonardis et al., 2015].

4.2 Genome Data: Acquisition and Alignment

The data used for both the full genome-wide covariation and the clade-specific genome-wide covariation was acquired from GISAID [Shu & McCauley, 2017]. We downloaded all 137636 available complete SARS-CoV-2 sequences on October 19, 2020. The resulting sequences were then aligned on the Biowulf Linux cluster at the National Institutes of Health, Bethesda, MD. MAFFT [Katoh et al., 2005] was used to align the sequences.

5 Acknowledgements

The authors would like to thank Prakriti Mudvari and Eli Boritz from the National Institute of Allergy and Infectious Diseases (NIAID) for help with data acquisition. Additionally, the authors would like to thank the HPC staff, Wolfgang Resch and Gennady Denisov for computational support using Biowulf. This work utilized the computational resources of the NIH HPC Biowulf cluster (<http://hpc.nih.gov>). This work was supported by the Intramural Research Program of the National Institute of Diabetes and Digestive and Kidney Diseases.

342 **6 Competing Interests**

343 The authors declare that they have no conflict of interest.

References

- [Briguglio et al., 2011] Briguglio, I., Piras, S., Corona, P., & Carta, A. (2011). Inhibition of RNA helicases of ssRNA+ virus belonging to Flaviviridae, Coronaviridae and Picornaviridae families. *International journal of medicinal chemistry*, 2011.
- [Dahirel et al., 2011] Dahirel, V., et al. (2011). Coordinate linkage of HIV evolution reveals regions of immunological vulnerability. *Proceedings of the National Academy of Sciences*, 108(28), 11530–11535, <https://doi.org/10.1073/pnas.1105315108>. <https://www.pnas.org/content/108/28/11530>.
- [De Leonardis et al., 2015] De Leonardis, E., Lutz, B., Ratz, S., Cocco, S., Monasson, R., Schug, A., & Weigt, M. (2015). Direct-Coupling Analysis of nucleotide coevolution facilitates RNA secondary and tertiary structure prediction. *Nucleic acids research*, 43(21), 10444–10455.
- [Ekeberg et al., 2014] Ekeberg, M., Hartonen, T., & Aurell, E. (2014). Fast pseudolikelihood maximization for direct-coupling analysis of protein structure from many homologous amino-acid sequences. *Journal of Computational Physics*, 276, 341–356.
- [Gallagher & Buchmeier, 2001] Gallagher, T. M. & Buchmeier, M. J. (2001). Coronavirus spike proteins in viral entry and pathogenesis. *Virology*, 279(2), 371–374.
- [Gorbalenya et al., 2020] Gorbalenya, A., et al. (2020). The species severe acute respiratory syndrome related coronavirus: classifying 2019-nCoV and naming it SARS-CoV-2. *Nat Microbiol* 5: 536–544.
- [Hoang et al., 2019a] Hoang, D.-T., Jo, J., & Periwai, V. (2019a). Data-driven inference of hidden nodes in networks. *Physical Review E*, 99(4), 042114.
- [Hoang et al., 2019b] Hoang, D.-T., Song, J., Periwai, V., & Jo, J. (2019b). Network inference in stochastic systems from neurons to currencies: Improved performance at small sample size. *Physical Review E*, 99(2), 023311.
- [Holland et al., 2020] Holland, L. A., et al. (2020). An 81-Nucleotide Deletion in SARS-CoV-2 ORF7a Identified from Sentinel Surveillance in Arizona (January to March 2020). *Journal of Virology*, 94(14), <https://doi.org/10.1128/JVI.00711-20>. <https://jvi.asm.org/content/94/14/e00711-20>.
- [Issa et al., 2020] Issa, E., Merhi, G., Panossian, B., Salloum, T., & Tokajian, S. (2020). SARS-CoV-2 and ORF3a: Nonsynonymous Mutations, Functional Domains, and Viral Pathogenesis. *Msystems*, 5(3).
- [John Hopkins University, 2020] John Hopkins University, J. (2020). Coronavirus Resource Center. <https://coronavirus.jhu.edu/>.

- 378 [Kang et al., 2020] Kang, S., et al. (2020). Crystal structure of SARS-CoV-2 nucleocap-
379 sid protein RNA binding domain reveals potential unique drug targeting sites. *Acta*
380 *Pharmaceutica Sinica B*.
- 381 [Katoh et al., 2005] Katoh, K., Kuma, K.-i., Toh, H., & Miyata, T. (2005). MAFFT version
382 5: improvement in accuracy of multiple sequence alignment. *Nucleic acids research*,
383 33(2), 511–518.
- 384 [Kwong et al., 2005] Kwong, A. D., Rao, B. G., & Jeang, K.-T. (2005). Viral and cellular
385 RNA helicases as antiviral targets. *Nature reviews Drug discovery*, 4(10), 845–853.
- 386 [Lu et al., 2010] Lu, W., Xu, K., & Sun, B. (2010). SARS accessory proteins ORF3a and
387 9b and their functional analysis. In *Molecular Biology of the SARS-Coronavirus* (pp.
388 167–175). Springer.
- 389 [Mercatelli & Giorgi, 2020] Mercatelli, D. & Giorgi, F. M. (2020). Geographic and Ge-
390 nomic Distribution of SARS-CoV-2 Mutations. *Frontiers in Microbiology*, 11, 1800,
391 <https://doi.org/10.3389/fmicb.2020.01800>. <https://www.frontiersin.org/article/10.3389/fmicb.2020.01800>.
- 393 [Morcos et al., 2011] Morcos, F., et al. (2011). Direct-coupling analysis of residue coevo-
394 lution captures native contacts across many protein families. *Proceedings of the National*
395 *Academy of Sciences*, 108(49), E1293–E1301.
- 396 [NCBI, 2020] NCBI (2020). Accession No: NC_045512.2. Severe acute respiratory syn-
397 drome coronavirus 2 isolate Wuhan-Hu-1. [https://www.ncbi.nlm.nih.gov/nucleotide/NC_](https://www.ncbi.nlm.nih.gov/nucleotide/NC_045512)
398 045512.
- 399 [Pedregosa et al., 2011] Pedregosa, F., et al. (2011). Scikit-learn: Machine Learning in
400 Python. *Journal of Machine Learning Research*, 12, 2825–2830.
- 401 [Shu & McCauley, 2017] Shu, Y. & McCauley, J. (2017). GISAID: Global initiative on
402 sharing all influenza data—from vision to reality. *Eurosurveillance*, 22(13), 30494.
- 403 [Song et al., 2019] Song, Z., et al. (2019). From SARS to MERS, thrusting coronaviruses
404 into the spotlight. *Viruses*, 11(1), 59.
- 405 [Tai et al., 2020] Tai, W., et al. (2020). Characterization of the receptor-binding domain
406 (RBD) of 2019 novel coronavirus: implication for development of RBD protein as a viral
407 attachment inhibitor and vaccine. *Cellular & molecular immunology*, 17(6), 613–620.
- 408 [Uğurel et al., 2020] Uğurel, O. M., Ata, O., & Balik, D. (2020). An updated analysis of
409 variations in SARS-CoV-2 genome. *Turkish Journal of Biology*, 44(SI-1), 157–167.

- 410 [Weigt et al., 2009] Weigt, M., White, R. A., Szurmant, H., Hoch, J. A., & Hwa, T. (2009).
411 Identification of direct residue contacts in protein–protein interaction by message passing.
412 *Proceedings of the National Academy of Sciences*, 106(1), 67–72.
- 413 [World Health Organization, 2020] World Health Organization, W. (2020). Coronavirus
414 disease (COVID-2019) situation re-ports. [http://web.archive.org/web/20080207010024/](http://web.archive.org/web/20080207010024/http://www.808multimedia.com/winnt/kernel.htm)
415 <http://www.808multimedia.com/winnt/kernel.htm>.
- 416 [Wu et al., 2020] Wu, A., et al. (2020). Genome composition and divergence of the novel
417 coronavirus (2019-nCoV) originating in China. *Cell host & microbe*.
- 418 [Zhou et al., 2020] Zhou, Y., Hou, Y., Shen, J., Huang, Y., Martin, W., & Cheng, F. (2020).
419 Network-based drug repurposing for novel coronavirus 2019-nCoV/SARS-CoV-2. *Cell*
420 *discovery*, 6(1), 1–18.
- 421 [Zhu et al., 2020] Zhu, N., et al. (2020). A novel coronavirus from patients with pneumonia
422 in China, 2019. *New England Journal of Medicine*.