Ratio-based sensing of two transcription factors regulates the transit to cell differentiation

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ABSTRACT

Cell state transitions depend on transcription factors to effect mRNA expression changes.
Although certain transitions are directed by change in absolute concentration of single
transcription factors, transitions in animal cells frequently require combinations of multiple
factors. To investigate how cells sense and respond to concentration changes of concurrently
expressed factors, we quantified the expression dynamics of the *Drosophila* transcription
factor activator-repressor pair Pnt and Yan during photoreceptor differentiation. Progenitor cells
maintain a constant ratio of Pnt-to-Yan despite extensive cell-to-cell variation in absolute protein
concentrations. A rapid and sustained increase in the ratio accompanies each progenitor cell as it
transitions to a photoreceptor state. Perturbations disrupting the ratio result in gains or losses of
these transitions. We used biophysical modeling to illustrate how a ratiometric system can
produce differential transcription factor binding necessary to drive transitions. Reliance on
relative rather than absolute concentration as the control variable may allow ratiometric systems
to function more robustly under conditions of component variability.
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INTRODUCTION

Organismal development proceeds through a sequence of cell state transitions that yield

increasingly tissue-specific cellular states. Cell states and the transitions between them are often

modeled as outcomes of a dynamical system. Cell states, typically characterized by their mRNA

and protein expression profiles, are regulated by transcriptional activators and repressors that

dynamically interact according to certain rules (1). Studies of cell state transitions underlying

numerous developmental decisions have identified the relevant transcription factors, elucidated

their regulatory relationships and organized them into networks bootstrapped from inferred

pairwise interactions. Although network diagrams provide static abstractions of cell state

transitions by linking input transcription factors to output mRNA and protein expression, on their

own they do not reveal the temporal dynamics or the quantitative rules that drive these decisions.

Notable progress has been made in understanding how unicellular organisms (2) and *in vitro*

cultured systems (3) respond to changes in transcription factor concentrations to execute state

transitions. These studies provide support for two distinct strategies. In the first, changes in the

absolute concentrations of key transcription factors provide ultrasensitive regulation and trigger

distinct differentiative cell state transitions (4–7). In the second, state transitions are regulated by

relative rather than absolute changes in single transcription factor concentrations (8, 9). Together

these studies provide conceptual insights on how a cell may sense individual transcription factor
concentrations and use changes in their levels to regulate the transit toward a particular state.

However, in complex multicellular eukaryotes, cells must sense and integrate the expression
dynamics of multiple transcription factors to make accurate cell state decisions. In such contexts
it is unknown whether cells use emergent properties such as ratiometric changes in transcription
factor levels to execute state transitions. Compounding the difficulty of answering this question,
simultaneous measurement of multiple transcription factor levels at single cell resolution, over the
time scales needed to follow a cell state transition, still presents a major technical barrier in most
multicellular developing tissues.

Unique features of the developing *Drosophila* eye allow us to overcome these challenges. We
focused our study on two ETS-family transcription factors, the activator Pointed (Pnt) and the
repressor Yan (also known as Anterior Open, or *Aop*), that compete for the same DNA binding
sites across the genome (10–20). This activator/repressor pair functions downstream of receptor
tyrosine kinase (RTK) signaling to regulate cell state transitions in many developing *Drosophila*
tissues, including progenitor to photoreceptor transitions in the eye (10–12, 21–28). During eye
development, eight distinct photoreceptor (R) neurons, R1-R8, are specified from a specific pool
of multipotent progenitor (P) cells that co-express Pnt and Yan and are poised to differentiate
(Figures 1A and S1A) (28). Each P cell to R cell transition, with the exception of the P to R8
transition, requires RTK signaling (29) to resolve the opposing transcriptional inputs from Pnt and
Yan on their shared target genes. During these transitions, concomitant downregulation of Yan
activity and upregulation of Pnt activity is thought to shift the state of a poised P cell in a pro-
differentiation direction toward a young R cell state (Figure 1A) (21–23, 29–31). Other
transcription factors combinatorially instruct each transitioning young R cell about which specific
R cell type to choose (10, 12, 32, 33).

In this study, we investigated how poised P cells sense and respond to changes in abundance of
Pnt and Yan proteins by measuring the expression dynamics of these two transcription factors in
thousands of individual nuclei during P to R cell state transitions. We find that P to R cell state
transitions are marked by a change in the relative ratio of the Pnt and Yan proteins. P cells maintain

a fairly constant ratio of Pnt-to-Yan protein levels over time despite extensive cell-to-cell variation

in the absolute protein levels. P cells that initiate transitions to R fates experience a rapidly

increasing ratio. As R cells mature, the Pnt-to-Yan ratio remains stably elevated above the ratio of

the remaining P cells. Confirming the biological importance of this observation, directed

perturbations that artificially change the ratio result in either gain or loss of cell state transitions

and defects in tissue patterning. We propose that cells in the developing eye rely on a ratiometric

sensing mechanism in which a sustained relative increase in the Pnt-to-Yan ratio initiates and

accompanies progenitor to differentiated state transitions.

RESULTS

Single cell *in vivo* measurements of activator and repressor transcription factor dynamics

connect protein abundance and cell states in a developing tissue.

The developing *Drosophila* eye provides a powerful *in vivo* context to causally link transcription

factor dynamics to cell states. Each eye contains a pool of ~20,000 undifferentiated progenitor (P)

cells from which a subset of ~6,000 transition to photoreceptor (R) cells. Within each eye, the

~6,000 R cells are organized into ~ 750 identical units called ommatidia, each containing the same

cohort of eight R cells (R1-R8). R cell differentiation and ommatidial formation begin in the

posterior margin of the larval eye, from which point a morphogenetic furrow (MF) sweeps across

the tissue with a constant velocity in the anterior direction. A new row of ommatidia forms every

~2 hours in the wake of the moving MF as it transits across the eye (Figures 1B). Within each

nascent ommatidium, the eight R cells differentiate from a local pool of P cells in a stereotypic

sequence: first R8, then R2 and R5, then R3 and R4, then R1 and R6, and finally R7 (Figure 1B

and S1A) (34, 35). Each R cell type can be reliably identified as soon as it becomes

morphologically and positionally distinct from the P cell population, which occurs before the onset

of detectable neuronal or photoreceptor-specific mRNA or protein expression (31). Remaining P

cells that do not transition to any of the R cell types during this period differentiate into other

ommatidial cell types at later stages. Together, all these features make it possible to follow the

temporal progression of thousands of individual P to R transitions simultaneously in a single fixed

tissue sample, allowing quantitative, single cell resolution-examination of the dynamical processes

that regulate these transitions.

To understand how P vs. R cell states are resolved, we measured Pnt and Yan levels simultaneously

in thousands of individual cell nuclei before, during, and after P to R transitions. Pnt levels were

measured using a functional GFP-tagged allele (28) while Yan levels were measured indirectly

using a monoclonal antibody that we had previously shown to be calibratable (31). We adapted

our previous approach (31) to convert the spatial position of each cell to a specific developmental

time. Given that the MF moves at constant velocity across the developing eye (36), we converted

the spatial position of the MF to developmental time t= 0, with each successive row of ommatidia

posterior to the MF marking successive 2 h intervals. Individual P and R cell types were identified

using their stereotyped morphology and the apical-basal position of their nuclei (Figure S1). Cross-

validation with cell type-specific markers showed our identification approach has an estimated >97%

accuracy for all P and R cell types (Table S1), matching our previous study (31). We refer to the

earliest identifiable cells within each R cell differentiation trajectory as "young" R cells and the

neighboring poised P cells from which they diverge as "concurrent" P cells. Although our approach

cannot measure the protein dynamics of an individual P cell transitioning to a specific R state in

real time, quantifying protein expression in hundreds to thousands of spatially ordered cells of

defined identities along the temporal trajectory provides a macroscopic view of dynamics from

which mechanistic principles can be extracted.

Pnt and Yan expression pulses coincide with critical windows of P to R cell state transitions.

We first measured Pnt and Yan expression dynamics in the P cell population (Figure 1C-E). In this

population, average expression levels of both Pnt and Yan increased immediately prior to the

initiation of R cell differentiation, reached maximal expression, and then slowly decayed. Pnt

expression peaked twice in P cells whereas Yan expression peaked once, in between the two Pnt

expression peaks. Despite their alternating maximal amplitudes, the overall induction and decay

of Pnt and Yan proteins were concurrent in P cells (Figure S2), consistent with our previous

qualitative observations (Lachance et al., 2014).

The first and second peaks of Pnt protein expression in P cells coincided with the two successive

waves of R cell differentiation (Figure 1C,F,H) (30). P cell transitions to R8, R2/R5, and R3/R4

occurred during the first Pnt peak (Figure 1C,F), while transitions to R1/R6, and R7 occurred

during the second peak (Figure 1C,H). All young R cells at these transition windows displayed a
25-50% increase in Pnt levels, which decayed as these cells matured over time. Yan showed the
opposite dynamical behavior during R cell differentiation; young R cells exhibited lower Yan
protein levels compared to concurrent P cells (Figure 1G,I). Yan levels rapidly decayed in
maturing R cells, reaching a basal level that was at least two-fold lower than that in concurrent P
cells. To summarize, pulses of the activator Pnt and the repressor Yan coincide with two windows
of P to R cell state transitions. Within these windows, a respective increase and decrease in Pnt
and Yan protein levels accompany the transitions.

P to R state transitions are robust to variation in Pnt and Yan protein levels.
We previously found that P to R state transitions are robust to systematic perturbation of absolute
Yan protein levels (22, 31). Could cell state transitions be similarly robust to changes in Pnt protein
levels? To answer this question, we decreased Pnt protein levels by reducing the *pnt* gene copy
number from two (wildtype) to one. As expected, having a single copy of the *pnt* gene resulted in
a ~ 50% reduction in Pnt protein levels compared to levels measured in animals with two copies
(Figure 2A,C). Pnt levels were not only reduced in P cells, but when R cells differentiated from
single-copy *pnt* P cells, there was a corresponding reduction in the maximal amplitude of Pnt levels
reached by these cells (Figure 2A,C). Notably, P to R state transitions were robust to this
significant reduction in Pnt protein levels, and eyes developed with a wildtype pattern and
morphology (Figure S3).

Unexpectedly, when we measured Yan levels in P cells in these single-copy *pnt* eyes, we found
that Yan protein levels were significantly reduced, despite these cells still having two copies of the
yan gene (Figure 2B,D). This suggests a role for Pnt in positively regulating Yan expression, and
perhaps a mechanism of coordinated regulation of Pnt and Yan abundance. The qualitatively
parallel behaviors of Pnt and Yan in this experiment prompted us to quantitatively assess the extent
to which Pnt and Yan levels are coordinated within individual nuclei. To do this, we calculated the
Pnt-to-Yan ratio in individual P cells at each P-to-R transition point and compared the results
between populations with one vs. two copies of the *pnt* gene. Consistent across the different
transition points, the Pnt-to-Yan ratios in single copy *pnt* P cells were remarkably similar to the
ratios in two-copy *pnt* P cells (Figure 2E).

A reset in the Pnt-to-Yan ratio coincides with P to R cell state transitions.

Given that the robustness of cell state transitions to systematic variation in *pnt* gene copy number

was accompanied by a stabilized Pnt-to-Yan ratio in P cells, we wondered if the ratio might act as

a control parameter regulating the transitions from P to R states. Consistent with this possibility,

the average Pnt-to-Yan ratio in P cells remained dynamically stable about a fixed value over time

(Figure 3A). Greater cell-to-cell fluctuations in the ratio coincided with the specific times when

Pnt and Yan levels peaked (Figures 3A and 1D,E).

We next asked whether the Pnt-to-Yan ratio was also invariant in R cells over time. We first

examined the ratio in R7 cells along their differentiation trajectory. Strikingly, the average Pnt-to-

Yan ratio was higher in young R7 cells relative to their concurrent P cells (Figure 3A, note log

scale of y-axis). The ratio rose and then gradually fell as R7 cell differentiation progressed over

time, but always remained at higher values than that of concurrent P cells. Examination of the Pnt-

to-Yan ratio dynamics in all other R cell types revealed a similar and consistent rapid increase as

R cells differentiated from the P cell pool, followed by a gradual decline to a new steady value that

was higher than that of concurrent P cells (Figure S4).

The stable Pnt-to-Yan ratio in P cells rapidly shifts to a new, higher ratio value as P cells transition

to become R cells, and subsequently stabilizes at that higher value in the R cells. This observation

prompted us to hypothesize that the ratio becomes destabilized during state transitions and then

re-set as cells stabilize their states. If so, then cell-to-cell heterogeneity of this ratio should rise

during the time-windows for state transitions, and then subside as cell states are resolved. We used

our established method (31) to quantify cell-to-cell heterogeneity of Pnt levels, Yan levels, and the

ratio along each P to R differentiation trajectory (Figure S5). We found increased heterogeneity in

the ratio, as quantified by the coefficient of variation, coincided with the time windows in which

subsets of P cells differentiated to R cells. The enhanced heterogeneity persisted in young R cells

and diminished as they matured.

We next focused on how ratio values are distributed in young R vs. concurrent P cells at the time

windows of cell state transitions. Interestingly, we found that there was a substantial overlap in

ratio values between young R cells and concurrent P cells in these time windows. Nevertheless,

the Pnt-to-Yan ratios of most young R cells were greater than the median ratio for the concurrent

P cells (Figure 3B-F). This resulted in a significantly higher average ratio in all young R cell types

relative to their concurrent P cell neighbors (Figure 3G, $P<0.001$, KS 2-sample test). Together

these measurements reveal that a subset of P cells transiently elevate their Pnt-to-Yan ratio at the

P-to-R state decision points, but that only young R cells maintain the elevated ratio as they mature.

Controlled perturbations of the Pnt-to-Yan ratio bias P cells towards or against R state

transitions.

If the Pnt-to-Yan ratio is a control variable that triggers P to R state transitions, then tuning up or

down the proportion of P cells that stably elevate the ratio should correspondingly change the

proportion of cells that transition to R states. As a first test of this hypothesis, we altered the RTK

signaling circuitry to artificially induce a ratio increase in a larger number of P cells at specific cell

state transition time-windows. We expressed a Ras^{V12} transgene encoding a constitutively active

version of the Ras GTPase under the control of the enhancer/promoter of the *sevenless* (*sev*) gene.

This induced transient expression of Ras^{V12} in subsets of P cells during the R3/R4 and R7 transition

points, and then stable expression in mature R3/R4 and R7 cells (Figures 4 and S6) (22, 37, 38).

By overriding the endogenous RTK circuitry, this perturbation should increase Pnt protein

abundance (Figure 4A). As predicted, $sev>Ras^{V12}$ dramatically increased the amplitude and

duration of the second peak of Pnt expression in P cells, which coincides with the second wave of

R cell differentiation events (Figure 4B). Yan protein levels were weakly reduced in P cells during

this time window (Figure 4D). The result was a sustained elevation in the Pnt-to-Yan ratio in a

larger number of P cells at the transition window and continuing thereafter (Figure 4C). $sev>Ras^{V12}$

expression also resulted in supernumerary R cells that had comparable ratios to neighboring R7

cells (Figure 4E). These ectopic R cells were typically found flanking the R7 cell of each

ommatidium (Figure S7A,B). Thus, forcing P cells to have an elevated Pnt-to-Yan ratio results in

too many P cells becoming R cells, consistent with the ratio being a key control variable that

regulates P to R state transitions.

To further test this hypothesis, we performed the converse experiment by preventing the Pnt-to-

Yan ratio from increasing in P cells during transition windows. We used the same *sev*

enhancer/promoter to drive expression of a constitutively active form of Yan, Yan[Act], which results
in accumulation of the repressor protein in the nuclei of R3/4 and R7 cells (Figure 5A) (22, 39)).
As expected, R8, R2/R5 and R1/R6 state transitions appeared normal and exhibited normal ratio
dynamics (Figures 5E and S8A-D,G,H). There was a mild increase in Yan levels and a delayed
increase in the Pnt-to-Yan ratio in young R3/R4 cells (Figures S8E,F). As these cells matured,
their ratios reached a steady state value that was comparable to wildtype R3/4 cells.

In contrast, the *sev>Yan[ACT]* perturbation resulted in a large reduction in the total number of R7
cells (Figure 5B-E). The few cells that could be plausibly identified as R7s were mostly young R7
cells. These young R7 cells had diminished Pnt-to-Yan ratios that were comparable to the ratio in
concurrent P cells (Figure 5C,D). Comparison of Yan and Pnt expression confirmed that the
reduced ratio in these young R7 cells was driven primarily by increased Yan levels (Figure S9).
Identifying mature R cells in the adult retina revealed an almost complete loss of R7s (Figures 5E
and S7A,C), firmly connecting the failed state transition to the inability of *Yan[ACT]* expressing P
cells to elevate the Pnt-to-Yan ratio.

Thermodynamic equilibrium modeling of transcription factor competition for DNA binding
suggests tuning the activator-to-repressor ratio can produce accurate control of
transcriptional outputs.
How could cells robustly regulate transcription of genes in response to the relative ratio of a
transcriptional activator such as Pnt and repressor such as Yan? Since both Pnt and Yan are ETS
family transcription factors with overlapping sequence specificity for DNA binding (10–16) the
underlying mechanism should reflect competition for binding sites in target gene promoters and
enhancers. Because measuring enhancer occupancy at single cell resolution *in vivo* is not yet
experimentally feasible, we instead investigated this mechanism *in silico*. We created a
mathematical model of the dependence of binding occupancy on the concentrations of a pair of
transcription factors that compete for common DNA binding sites. If the activator and repressor
compete for occupancy with the same binding affinity, and binding sites are saturated, then
equilibrium occupancy by either factor will be more sensitive to the relative concentration of the
two factors than to the absolute concentration of both species (Figure S10; see Methods).

However, the situation with Pnt and Yan is more complex. While there are several well-documented target genes that contain enhancers with common binding sites for Pnt and Yan (10–12), Yan binds these sequences with higher affinity than Pnt (12). Moreover, recent experiments suggest Yan and Pnt differentially interpret the structural syntax of cis-regulatory modules (19). This complex phenomenon is a consequence of cooperative interactions between DNA-bound Yan molecules. Specifically, Yan monomers are able to self-associate via their sterile alpha motifs (SAM), enabling DNA-bound Yan monomers to stabilize the recruitment of additional Yan monomers to adjacent sites (19, 40). Because Pnt does not self-associate (41, 42), Yan-Yan cooperativity will bias the activator vs. repressor competition for binding sites.

To evaluate this possibility, we adapted a modeling framework developed to probe the effects of *cis*-regulatory syntax on Yan binding site occupancy (43). The model considers an ensemble of microstates, each defined by a unique configuration of vacant or Yan-bound sites. Each microstate is assigned a thermodynamic potential based on the cumulative influence of strong sequence-specific binding to consensus ETS sites, weak non-specific DNA binding, and SAM-SAM polymerization. We generalized the Hope et al. model by incorporating Pnt as a second transcription factor that competes for occupancy of the same binding sites but does not self-associate (Figure S11A,B). Using this model, we explored how Yan-Yan cooperativity might impact Pnt binding site occupancy to changes in the activator-to-repressor ratio at the enhancer.

We first considered a scenario in which neither Yan nor Pnt exhibit cooperativity (Figure 6A). In the absence of stabilizing SAM-SAM interactions, the landscape of overall binding site occupancy was identical to that obtained with the simple binding model described above (Figures 6A and S11). Increasing the Pnt-to-Yan ratio resulted in a gradual increase in Pnt occupancy for all individual binding sites, producing a titration contour closely resembling a Michaelian curve (Figures 6C and S11C).

Introducing stabilizing SAM-SAM interactions for Yan dramatically sharpened the transition from Yan to Pnt occupancy dominance (Figure 6B). Weighting the energetic contributions of binding strength and polymerization by the statistical frequency of each microstate revealed that the

transition was driven by an abrupt change in the dominant binding mechanism. Polymerization-
associated cooperativity effects dominate binding site occupancy when the Pnt-to-Yan ratio is low,
while binding strength dominates when the ratio is high (Figure S11D).

Increasing the Pnt-to-Yan ratio revealed nonlinear transitions from low to high Pnt occupancy for
each individual binding site (Figures 6C and S11E). These transitions resembled Hill function
forms, with sharp thresholds delimiting distinct transcriptional outputs. At low activator-to-
repressor ratios, Yan occupancy dominated, while at some critical ratio, Pnt-bound molecules
prevented Yan-Yan interactions, ultimately allowing Pnt to outcompete Yan as the ratio increased
further. If transcription factor levels are sufficient to saturate binding sites, then relative occupancy
by Pnt and Yan should be agnostic to changes in the absolute abundance of either factor, as long
as the ratio remains constant.

Because the model was designed to complement rather than recapitulate our *in vivo* measurements
of transcription factor expression dynamics, its predictions about molecular mechanism can only
provide guidance on how to interpret the experimental data. For example, our comparisons of the
Pnt-to-Yan ratio in young R cells relative to the concurrent P cell population (Figures 3B-F) can
be viewed as parallel representations to the phase spaces calculated in the model (Figures 6B).
Above a certain activator-to-repressor ratio, cells will transition to a new state, while below that
threshold, they will remain in the initial state, regardless of the absolute transcription factor
concentrations (Figures 6D,E). In this way, small changes in the relative ratio of Pnt-to-Yan would
drive cell state changes by eliciting large changes in DNA binding site occupancy, while large
changes in absolute Pnt and Yan levels would have little effect so long as the relative ratio remains
constant.

DISCUSSION
Our study has quantitatively analyzed *in vivo* a series of cell state transitions that are controlled by
the abundance ratio between an activator transcription factor and a repressor transcription factor.
In this multicellular developing system, cells in the progenitor pool (P cells) maintain a
dynamically constant Pnt-to-Yan ratio necessary to sustain the undifferentiated state. RTK
signaling changes the ratio set-point and produces a sustained increase in the ratio, at the same

time as it is driving a P cell's transition to differentiation. In this way the relative ratio would

directly control the makeup of transcription factor complexes on target genes required for R cell

fates, with low Pnt-to-Yan ratios favoring transcriptional repression of target genes and high ratios

favoring their transcriptional activation. We support this description with *in vivo* experiments in

which we show that the changes in ratio associated with correct cell differentiation can take place

at different absolute concentrations of the transcription factors. Indeed, our experiments

demonstrate that the Pnt/Yan system is able to maintain a fixed ratio and to make correct transitions

over at least a four-fold range of activator and repressor abundance.

Several features of the Pnt/Yan system may reflect general requirements for any ratiometric-based

control mechanisms. First, the regulators must be co-expressed, compete for the same molecular

partners and exert opposite effects on them. In eye cells, Pnt and Yan compete for the same DNA

binding sites to respectively activate and repress target gene transcription. Second, distinct states

must be mechanistically associated with specific ratio values. In our case, a lower activator-to-

repressor ratio connects repressor-dominated DNA occupancy to maintenance of the progenitor

state, while a higher ratio couples activator-dominated occupancy to differentiation. Third, to

induce a new state, the initial ratio set-point point must be changed. In our system, the initial set

point in P cells is buffered by a compensatory mechanism that keeps the ratio dynamically stable.

During the transit to differentiation, RTK signaling increases the ratio, most likely by differentially

regulating the synthesis and degradation of Pnt and Yan through a combination of transcriptional

and posttranscriptional mechanisms (44). To override the progenitor state ratio set point, signaling

must induce changes that are different either in kind and/or in magnitude from those that set the

initial ratio. Fourth, for a system to be controlled by molecular ratios rather than by absolute

concentrations, its output must rely on the probability of binding of the two transcription factors

to common DNA sites or partners, which is dictated by their relative concentrations. Finally,

incorporating cooperativity can make a ratiometric system tunable and sensitive to small changes

in the ratio.

In silico modeling of a Pnt/Yan-like system suggests that stabilizing interactions between repressor

molecules bound to adjacent DNA sites could sensitize enhancer occupancy to the relative

abundance of the competing transcription factors. Indeed, prior work has shown that DNA-bound

Yan monomers enhance recruitment of Yan to adjacent binding sites through stabilizing protein-
protein interactions (19, 40). As shown in our model, such cooperativity makes the system
sensitive to small but sustained relative changes, leading to non-linear (ultrasensitive and
threshold-like) changes in site occupancy that can drive a state transition. These general ratiometric
system features could be readily incorporated into transcriptional networks with more than two
regulators and more generally could provide robust regulation to a broad spectrum of biological
processes that require precise combinatorial interactions between competing regulatory factors.
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An unexpected discovery in our experiments is the ability of the Pnt/Yan system to maintain a
fixed ratio and to make correct transitions over at least a four-fold range of activator concentration.
This predicts a stabilizing mechanism that monitors the relative ratio of Pnt and Yan and takes
corrective action when the ratio deviates from a specified reference value. The molecular nature
of the stabilizing mechanism in P cells and the means by which it is modified so that R cells can
increase and maintain an elevated ratio are currently unknown but could involve both
transcriptional and post-transcriptional feedback. For example, a simple way to couple Yan levels
to Pnt would be a positive feedback loop in which Pnt transcriptionally activates *yan*. Positive
feedback-based architecture is often incorporated into transcriptional regulatory circuits that
control cell differentiation and can filter transient fluctuations (noise) in the levels of individual
components to prevent random transitions (45, 46). Based on the multiple layers of positive and
negative feedback regulation within the Pnt/Yan network (16, 17, 30, 44, 47), more elaborate
mechanisms are possible.
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Previous studies have found cells can sense and respond to relative concentration changes of
individual molecular species using fold-change detection (9, 48–53). These studies suggest that to
compute fold-change of a single type of protein, cells use specific regulatory circuits to first
"measure" and establish a molecular memory of the state of one variable, and later compare it to
a new measurement of the same variable (54). In contrast, cells in the eye system concurrently
compare the levels of two different transcription factors rather than measure the fold-change of
each factor over time. Identifying the specific network features that enable ratiometric detection
in the Pnt/Yan system and measuring the transcription response dynamics of individual target
genes to changes in Pnt-to-Yan ratios will provide important tests of our model. Given the broad

reliance of cell state transitions on combinatorial regulation, ratiometric control may prove to be a

common and effective developmental strategy for ensuring their accuracy and robustness.

EXPERIMENTAL PROCEDURES

Genetics

Unless otherwise noted, all experiments were performed with animals reared at 25°C on standard

cornmeal-molasses *Drosophila* culture medium. Fly stocks from the Bloomington Stock Center:

pnt-GFP BAC transgene, BL42680; *pnt²*, BL2222; H2Av-mRFP BL23650, pnt$^{\Delta 88}$ (21);

sev>Ras^{v12} (37); *sev>Yan^{ACT}* (22); *sev>Gal4* (55). Measurements of wild type dynamics of Pnt-

GFP were made in eye discs from *w^{1118}; pnt-GFP; pnt$^{\Delta 88}$/pnt², H2Av-mRFP*. The effect of *pnt* gene

dosage on Pnt-to-Yan ratio was measured in *w^{1118}; pnt-gfp /+ ; pnt$^{\Delta 88}$/pnt²* (1x *pnt*) and *w1118;

pnt-gfp; pnt$^{\Delta 88}$/pnt²* (2x *pnt*) discs. In experiments with *Ras^{v12}* or *Yan^{ACT}*, Pnt-GFP and Yan levels

were measured in eye discs from animals of the following genotypes: *w^{1118}; pnt-gfp/ sev>Ras^{v12};

pnt$^{\Delta 88}$/+* relative to *w^{1118}; pnt-gfp / +; pnt$^{\Delta 88}$/+*; and *w^{1118}; pnt-gfp/sev>Yan^{ACT}; pnt$^{\Delta 88}$/+* relative

to *w^{1118}; pnt-gfp/ +; pnt$^{\Delta 88}$/+.*

Immunohistochemistry

All eye-antennal discs were dissected from white prepupae. For experiments in which 4′,6-

diamidino-2-phenylindole (DAPI) was used as the nuclear marker, samples were fixed in 4%

paraformaldehyde (w/v) / PBS-Triton X-100 0.1% (v/v) for 25 minutes at room temperature. After

fixation, eye discs were blocked in PBS-Triton X-100 0.1% (v/v) and 1% (v/v) normal goat serum

for 30 minutes at room temperature. Primary and secondary antibodies were incubated each for 2

hours at room temperature with DAPI. Including DAPI during primary and secondary antibody

staining was important for even penetration of DAPI. Antibodies used: mouse anti-Yan 8B12

(DHSB, 1:200) and goat anti-mouse Cy3 (1:2000, Jackson Immunoresearch). Discs were washed

for 20 min in PBS-Triton X-100 0.1% (v/v), and mounted in VectaShield Antifade mounting

medium (Vector Laboratories). To avoid rapid changes in cell volume, which would affect relative

fluorescence measurements, the substitution of PBS-Triton X-100 with Vectashield was done

gradually using increments of ~33% in VectaShield concentration. For experiments in which

H2Av-mRFP was used as the nuclear marker, discs were fixed in 4% (w/v) paraformaldehyde/PBS

for ~45 min and goat anti-mouse Pacific Blue antibody (Life Technologies, 1:200 dilution) was

used as the secondary antibody.

Samples were imaged within 18-24 hr after fixation. 1024 x 1024 16-bit images were captured

using either a Zeiss LSM880 or a Leica SP5 confocal microscope equipped with 40X oil

objectives. Discs were oriented with the equator (dorsal-ventral boundary) parallel to the x-axis of

the image. Optical slices were set at 0.8μm (45-60 optical slices per disc) with an additional digital

zoom of 1.2-1.4. Images recorded a region of at least 6 rows of ommatidia on each side of the

equator. All discs for a given perturbation were fixed, mounted, and imaged in parallel with control

discs to reduce measurement error. Sample preparation, imaging, and analysis were not performed

under blind conditions, nor was sex of the animals noted at time of dissection.

Quantification of expression levels

A minimum of three experimental replicate eye discs were imaged for each experimental

condition, with the exception of the *sev>Ras^{V12}* condition for which only one control disc was

used. For each wild type eye disc, ~160 R8, ~320 R2/5, ~300 R3/4, ~260 R1/6, ~ 220 R7 and

>1000 progenitor cells were manually selected from a set of computationally 2D-segmented

nuclei using Silhouette. The fluorescence intensity of each nucleus was measured by our

established procedure (Peláez et al 2015). Our new pipeline includes Silhouette, an open-source

package for macOS that integrates our image segmentation algorithm with a GUI (graphical user

interface) for cell type annotation (available at:

https://www.silhouette.amaral.northwestern.edu/). Subsequent analysis and visualization

procedures were carried out using the accompanying FlyEye python package, which is freely

available on GitHub. The resulting expression dynamics were inferred from confocal image

stacks using an updated version of the segmentation and annotation pipeline described in (31)..

Empirically, the replicate number of three eye discs provided reproducible composite dynamics.

No outlier eye discs were found for any experimental condition, so all samples were pooled,

temporally aligned and included in the analysis. The sample size was not pre-computed before

data collection.

Nuclear segmentation was performed using either H2Av-mRFP (Figures 1, 3, 4, S1-S2, S4 and
S5) or DAPI (Figures 2, 5 and S7-S9) as a reference channel to identify individual nuclear
boundaries. Nuclei expressing H2Av-mRFP were segmented using the Silhouette app's optimized
implementation of the GraphCut algorithm (56), while DAPI-stained discs were segmented using
an open-source implementation of the watershed algorithm designed to mitigate the effect of bright
spots caused by DAPI accumulation in nucleoli (57). Each layer of the confocal stack was
segmented in 2D independently in both cases. For each nucleus measured, a single contour was
manually selected and assigned a cell type (cell state) using Silhouette, with care taken to avoid
annotating nucleolar contours rather than complete nuclear contours in DAPI-stained discs. Since
each nucleus spans multiple optical sections, contours were always selected in the middle of the
nucleus. The population of progenitor cells was measured in multiple layers to include cells whose
nuclei were at different positions in the Apical -Ventral axis of the eye disc. In all cases each
nucleus was measured only in one layer to avoid measurement pseudoreplication.
481
Cells were identified and annotated by nuclear position in xyz space and shape using the His2Av-
mRFP channel with the other channels turned off. marker protein channel turned off. To validate
the accuracy of this method of cell identification / annotation, cells were also immunostained for
various cell-type specific marker proteins, as noted in Table S1. Annotations made with tie
His2Av-mRFP channel were then compared to the cell-type specific markers visualized in other
channels.
488
489   For each annotated nucleus contour, expression measurements were obtained by normalizing the
490   mean fluorescence of the Pnt-GFP and Yan antibody channels by the mean fluorescence of the
491   reference channel used for segmentation (DAPI or His2Av-mRFP). This normalization mitigates
492   variability due to potentially uneven sample illumination, segment area, nuclear volume, and in
493   the case of His-RFP, differences in protein expression capacity between cells.
494

Conversion of distance to time

Cell positions along the anterior-posterior axis were mapped to developmental time as described
previously (31). This is predicated on two assumptions: the furrow proceeds at a constant rate of
one column of R8 neurons per two hours; and minimal cell migration occurs. For each disc,

Delaunay triangulations were used to estimate the median distance between adjacent columns of

R8 neurons (58). We used the median rather than the mean distance because it minimized the

influence of non-adjacent R8s that were falsely identified by the triangulation (31). Dividing the

furrow velocity of 2 h per column by this median distance yields a single conversion factor from

position along the anterior-posterior axis to developmental time. This factor was applied to all cell

measurements within the corresponding disc, yielding expression time series. Notably, these are

not single cell dynamics, but rather aggregate dynamics across the development time course of a

spatially organized cell population.

Computation of moving averages and confidence intervals

Moving averages were computed by first-order Savitzky-Golay filtration (59). This method

augments the simple windowing approach used in (31) by enabling visualization of expression

trends at early time-points that are otherwise obscured by large window sizes. A secondary first-

order filtration with one-fifth the original window size was applied to smooth lines for

visualization purposes. None of our conclusions are sensitive to our choice of filtration or

smoothing method. Primary window sizes of 250 and 75 cells were used for reporting the

expression of multipotent and differentiated cells, unless noted otherwise. Confidence intervals

for the moving average were inferred from the 2.5th and 97.5th percentile of ten-thousand-point

estimates of the mean within each window. Point estimates were generated by bootstrap

resampling with replacement of the expression levels within each window.

Alignment of expression data

To align multiple eye disc samples, cells of each sample were aligned with a reference

population by shifting them in time. The magnitude of this shift was determined by maximizing

the cross-correlation of progenitor Pnt-GFP expression $Y(t)$ with the corresponding reference

time series $X(t)$. Rather than raw measurements, moving averages within a window of ten cells

were used to improve robustness against noise. This operation amounts to:

$$z = \underset{dt}{\mathrm{argmax}} \ \hat{\gamma}_{X(t),Y(t)}$$

$$\hat{\gamma}_{X(t),Y(t)}(dt) = E\left[\frac{(Y(t+dt) - \mu_Y)(X(t) - \mu_X)}{\sigma_Y \sigma_X}\right]$$

where, μ and σ are the mean and standard deviation of each time series, and dt is the time shift by

which the population should be shifted.

For each experimental treatment, a disc was randomly chosen and shifted in time such that time

zero corresponds to the first annotated R8 neuron. This disc then served as the reference

population for the alignment of all subsequent biological replicates within the treatment.

Similarly, different experimental treatments (e.g. control and perturbation) were aligned by first

aligning the discs within each treatment, then aggregating all cells within each treatment and

repeating the procedure with the first treatment serving as the reference.

This approach differs from the previous implementation of our pipeline in which discs were

manually aligned by the inflection point of their Yan-YFP expression profiles (31). Manual

alignment entails arbitrary prioritization of certain dynamic features over others. Our revised

protocol yields consistent, reproducible alignment of expression time series that equally weighs

the entire time course. The automated approach is more principled but less robust than the

manual approach. Specifically, it fails when dynamic forms qualitatively differ between

experimental treatments. In these instances, we revert to manual alignment using the inflection

point of Pnt-GFP induction as a reference.

Simple competitive binding model

Figure S10 presents results for an equilibrium model of two species, Yan (Y) and Pnt (P),

competing for a finite pool of shared binding sites, S:

$$Y + S \xrightleftharpoons{K_{D,Yan}} SY$$

$$P + S \xrightleftharpoons{K_{D,Pnt}} SP$$

546   where $K_{D,Yan}$ and $K_{D,Pnt}$ are equilibrium association constants and SY and SP denote the bound

547   species. Applying a mass balance to the total protein and binding site (S_0) abundances:

$$Y_0 = Y + SY$$

$$P_0 = P + SP$$

$$S_0 = S + SY + SP$$

549   yields an analytically tractable system of nonlinear equations (60). For each pair of absolute

550   protein abundances (Y_0, P_0), the Pnt binding site occupancy is simply SP/S_0.

Competitive binding model with cooperativity

The model presented in Figures 6 and S11 expands upon the work of (43). The model is based on

a single cis-regulatory element consisting of n adjacent binding sites, each of which may be

designated as ETS or non-ETS. Each binding site may exist in one of three binding states; bound

by a single copy of Yan, bound by a single copy of Pnt, or unbound. Thermodynamic potentials

were assigned to each binding state using two parameters for each transcription factor. The

parameter αX defines the free energy of transcription factor X binding to an ETS site,

while βX defines the free energy of binding to a non-ETS site. A unique configuration of binding

states for all n binding sites constitutes a single microstate, k. The thermodynamic potential of

each microstate was taken to be the sum of thermodynamic potentials for each of its constituent

binding sites. For each microstate, the stabilizing effect of polymerization was incorporated via a

third parameter, γX, that defines the free energy of SAM-SAM binding between a pair of similar

transcription factors bound to adjacent sites. The net result is a total thermodynamic

potential, ΔGk, for each microstate. An example enumeration of all possible microstates for an

element consisting of one ETS site preceding two non-ETS sites is provided in Figure S11B. The

statistical frequencies of each microstate were evaluated by constructing a canonical ensemble:

$$p_k = \frac{exp(\frac{-\Delta G_k}{RT})[P]^{a_P(k)}[Y]^{a_Y(k)}}{\sum\limits_{k} exp(\frac{-\Delta G_k}{RT})[P]^{a_P(k)}[Y]^{a_Y(k)}}$$

in which pk is the statistical frequency of microstate k, $[P]$ is the Pnt concentration, $[Y]$ is the

Yan concentration, $aP(k)$ and $aY(k)$ are functions representing the number of bound molecules

of P and Y within microstate k, T is a fixed temperature set to 300 K, and R is the gas constant.

Fractional occupancies for each binding site correspond to the cumulative statistical frequency of

all microstates in which the site is occupied by a given transcription factor. Overall fractional

occupancies are similarly evaluated across all sites within the element.

We considered regulatory elements comprised of 12 binding sites in which only the first site

carries the ETS designation. We retained the same parameterization of Yan binding used by

(43): αY=-9.955 kcal mol^{-1}, βY=-5.837 kcal mol^{-1}, and γY=-7.043 kcal mol^{-1}. We parameterized

Pnt binding thermodynamics to provide balanced competition between Pnt and Yan in the

absence of any SAM-mediated polymerization of Pnt. That is, we set Pnt binding affinities such

that the transition from Pnt to Yan occupancy occurs when Pnt and Yan concentrations are

approximately equal. The model used to generate Figure 6B assumes that Pnt binds individual

sites with elevated affinities $\alpha P = 0.96(\alpha Y + \gamma Y)$ and $\beta P = 0.96(\beta Y + \gamma Y)$. The model used to

generate Figure 6A uses these same elevated binding affinities for Yan, while setting γY=0 kcal

mol^{-1}. Qualitatively, our results are not sensitive to this parameterization.

Statistical frequencies of all microstates were enumerated using a recursive graph-traversal

algorithm implemented in python, where each node in the graph represents an individual binding

site and each edge reflects occupancy by a specific transcription factor. An open-source python

implementation of this modeling framework has been published on GitHub

(https://doi.org/10.5281/zenodo.5520493).

Data and software availability

All segmented and annotated eye discs will be deposited in a data repository upon publication. A

series of Jupyter notebooks that use these data to reproduce all analysis, simulations, and figures

presented in this manuscript has also been made available

(https://github.com/sbernasek/pnt_yan_ratio).

The Silhouette app used to segment nuclei in eye discs expressing His-2Av-mRFP and annotate

nuclei in all eye discs is freely available via the macOS App Store, while the FlyEye python

package used to generate, align, and visualize expression dynamics has been published on

GitHub (https://doi.org/10.5281/zenodo.5520468). Data are deposited at

https://datadryad.org/stash/share/ FrDw4tWe_ddlP7ATp3oYEvLG6FMe_3XAvNkbp9Ma2fk.

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756 **FIGURE LEGENDS**
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758 **Figure 1. Measuring Pnt and Yan expression in thousands of single cells defines two waves of cell state transitions**
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761 **(A)** Schematic summary of RTK-mediated regulation of P to R fate transitions. Poised P cells co-express Pnt and Yan in their nuclei (left panel). In response to a strong RTK signal, young R cells increase Pnt and decrease Yan (right panel).
764 **(B)** Schematic of a developing eye imaginal disc dissected from an animal ~100 hours post fertilization (25°C). Differentiation is initiated by passage of the morphogenetic furrow (MF), which moves across the eye epithelium from posterior to anterior (white arrow). Anterior P cells (dark blue) proliferate asynchronously, while P cells posterior to the furrow (light blue) arrest in G1, and some of them undergo a stereotyped sequence of state transitions. Specification of

regularly spaced R8 cells (red dots) marks the start of ommatidial assembly and is followed by
recruitment of additional R cell types (yellow dots). Adapted from Peláez et al. (2015).
(C) Maximum intensity projection of Pnt-GFP fluorescence in wild type eye disc oriented anterior
to the left and dorsal up. Right panel shows zoomed view of region marked by dashed white lines.
Arrival of the MF (white arrow) initiates cell fate transitions in the regions marked by the two
pulses of peak Pnt-GFP expression (black bars, labeled 1 and 2). Anterior-ward movement of the
MF allows tracking of P to R1-R8 cell state transitions across developmental time.
(D-E) Measured **(D)** Pnt-GFP and **(E)** Yan expression dynamics in individual P cell (grey) and R7
cell (purple) nuclei. P cells are present across the entire developmental time (grey arrow). A subset
transition to R7 cells which persist over time (purple arrow). Solid black lines are smoothed
moving averages across 250 and 75 individual nuclei for P and R7 cells, respectively. Black bars
labeled 1 and 2 denote the two pulses of peak Pnt-GFP in P cells. Shaded vertical stripes highlight
these two regions, which coincide with transition of P to various R fates shown in **F- I**.
(F-I) Dynamics of **(F,H)** Pnt-GFP and **(G,I)** Yan expression in **(F,G)** R8 (green), R2/R5 (blue)
and R3/R4 (orange) cells and **(H,I)** R1/R6 (red) and R7 (purple) cells. Grey denotes P cells. Lines
are smoothed moving averages across individual nuclei, backed by 95% confidence intervals for
the mean. Subsets of P cells transition into distinct R fates at different time points and span the
developmental time from thereafter, as indicated by colored arrows.
787
788 **Figure 2. Pnt-to-Yan ratio in P cells buffers against reduced Pnt dosage**
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(A-D) Moving averages of **(A, C)** Pnt-GFP and **(B, D)** Yan expression levels in P and R cells with
two copies **(A, B)** versus one copy **(C, D)** of the *pnt-GFP* gene. Measurements were made from
segmented nuclei marked by DAPI. Colors denote cell type. Shaded regions are bootstrapped 95%
confidence intervals for the moving averages (solid lines).
(E) Comparison of Pnt-to-Yan ratios between P cells with one copy (1x, light grey filled boxes)
versus two copies (2x, dark grey filled boxes) of *pnt-GFP* during time-windows of cell fate
transitions. Colors denote transition periods for each R cell type. These time periods were defined
in each disc by the times spanned by the first ten identifiable R cells. The concurrent P cell
populations were measured from these time windows. Pnt-to-Yan ratios in P cells are statistically
indistinguishable between gene dosages during R8, R2/R5, and R1/R6 cell fate transitions (P>0.1,
KS 2-sample test).
801
802 **Figure 3. Increased Pnt-to-Yan ratio accompanies P to R fate transitions**
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(A) Log2-transformed Pnt-to-Yan ratio dynamics in P (grey) and R7 (purple) cells with their
moving averages (solid black lines). Young R7 cells are the earliest subset of R7 cells that are
present in the timespan of the first ten identifiable R7 cells.
(B-F) Joint distributions of Pnt-GFP and Yan protein levels for young **(B)** R7, **(C)** R8, **(D)** R2/R5,
(E) R3/R4, and **(F)** R1/R6 cells. For each R cell type, the ten earliest identifiable R cells in each
sample mark the time span of young R cells. Progenitor cells that fall within the time window
spanned by these young R cells were designated as concurrent progenitors (grey). Black line
denotes the median Pnt-to-Yan ratio among the progenitor cells shown.
(G) Comparison of Pnt-to-Yan ratio levels between young R cells (color filled boxes) and their
concurrent progenitors (grey filled boxes). Colors denote R cell types. Asterisks indicate
significant differences (P<0.001, KS 2-sample test).

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Figure 4. Ectopic increase in Pnt-to-Yan ratio biases P cells towards R fates
(A) Schematic of the sev>Ras^{V12} perturbation in a subset of P cells, as well as R7 and R3/R4
cells. **(B-D)** The effects of Ras^{V12} signaling on **(B)** Pnt-GFP and **(D)** Yan in P cells increases the
(C) Pnt-to-Yan ratio. Lines are moving averages across 250 sequential cells. Shaded regions are
bootstrapped 95% confidence intervals for the mean. Solid lines and grey shading denote wildtype
controls. Dashed lines and red shading denote constitutive Ras signaling by *sev>Ras^{V12}*. Black
bars denote the second Pnt-GFP pulse which overlaps with the period of P to R7 fate transitions.
Red lines indicate the time period spanned by Ras^{V12} expressing cells. We previously reported a
modest increase in the duration of Yan-YFP expression in *sev>Ras^{V12}* P cells (Peláez et al. 2015),
but this difference was not detected using the Yan antibody. **(E)** Comparison of Pnt-to-Yan ratios
between wildtype and *sev>Ras^{V12}* P cells (grey filled box) concurrent with young R7 cells (purple
bordered box) as well as the first 24 ectopic unidentified R cells (light blue bordered box) in
sev>Ras^{V12} discs.
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Figure 5. Failure to increase the Pnt-to-Yan ratio biases P cells against R fates
(A) Schematic of *sev>Yan^{ACT}* that expresses MAPK-resistant Yan^{Act} protein in a subset of P cells,
as well as R7 and R3/R4 cells. **(B-C)** Dynamics of the log-2 transformed Pnt-to-Yan ratio in P
and R7 cells in **(B)** wildtype control and **(C)** *sev>yan^{ACT}* discs. Solid black lines are moving
averages across 250 and 75 sequential cells for P cells (grey dots) and R7 cells (purple dots),
respectively. Black bars denote the second Pnt-GFP pulse which overlaps with the period of P to
R7 fate transitions. Red lines indicate the time period spanned by Yan^{Act} expressing cells.
(D) Comparison of the Pnt-to-Yan ratios in P cells concurrent with remaining R7 cells in
sev>Yan^{ACT} discs. We include all P and R7 cells observed between 15 and 20 h
in **(B,C)**. **(E)** Cumulative abundance of each annotated R cell type as a function of developmental
time in wildtype (top) and *sev>Yan^{ACT}* (bottom) discs. Counts are normalized by the total number
of R8 cells detected across the time-course, and R2, R5, R3, R4, R1, and R6 cells are each tallied
separately. Colors denote R cell type. Shading denotes bootstrapped 95% confidence intervals for
each contour. R7 cells were not detected in approximately 85% of *sev>Yan^{ACT}* ommatidia.
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Figure 6. Cooperative DNA-binding by Yan sensitizes enhancer occupancy to the Pnt-to-Yan
ratio
(A) Illustration of the competition between Pnt and Yan for occupancy of mutual binding sites in
the absence of Yan polymerization (left). Overall binding site occupancy calculated as a function
of transcription factor abundance in the absence of Yan polymerization (right).
Color scale reflects overall Pnt site occupancy. We use a diverging scale because all sites are
fully saturated at total transcription factor concentrations above 1 nM. Under the range of
conditions shown, this implies that Yan occupies all sites left vacant by Pnt. Simultaneous
proportional increases in absolute abundance of both species have minimal impact on Pnt
occupancy (dashed arrow), while varying ratio confers gradual change (solid arrow).
(B) Illustration of competition between Pnt and Yan for occupancy of mutual binding sites when
Yan polymerizes (left). Overall binding site occupancy calculated as a function of transcription
factor abundance when Yan polymerizes (right). Color scale and arrows as in **(A)**. Note how the
sharpness of the transition is greatly increased when Yan polymerizes.

(C) Average Pnt occupancy across all binding sites as a function of Pnt-to-Yan ratio in the
absence of Yan polymerization (black line) vs. when Yan polymerizes (pink line). The contours
correspond to vertical paths traversed across panel **A** (right) and panel **B** (right) at a fixed Yan
concentration of 50 nM. Also see Figure S11.
(D) Probability density function of measured Pnt-GFP and Yan levels for the combined
populations of all young R cells (red) and their concurrent P cells (black). Contours decrease in
opacity with decreasing density and are not shown for values below 0.1. Density function is
estimated using Gaussian kernels with a bandwidth selected using Scott's rule. Thin diagonal
line of constant Pnt-GFP-to-Yan ratio is shown to aid interpretation
(E) Mean measured Pnt-GFP and Yan levels for the combined populations of all young R cells
(red) and their concurrent P cells (black), sampled from eye discs containing either one (*1x Pnt*)
or two (*2x Pnt*) gene copies of *pnt-GFP*. Horizontal and vertical lines about each point denote
the standard errors of the means.
873
874 **SUPPLEMENTARY FIGURE LEGENDS**
875
Figure S1. Identification of cell nuclei in eye discs.
(A) Top, cartoon of an apical view of the sequential differentiation of the eight R cell types (R1-
R8, various colors) from multipotent P cells (grey) and their relative positions within a single
ommatidium. Arrows denote RTK signals transmitted from the R8 to nearby P cells. Bottom, a
cross-section view through an eye disc, showing the epithelial constriction that marks the MF
(boxed region) and then the relative apical-basal nuclear positions of P cells (grey) and specified
R cells (various colors). Together, these and other stereotyped features enable unambiguous
identification of each cell type. Adapted from Peláez et al. (2015).
(B-F) Quantitative analysis pipeline showing microscopy and segmentation of a representative
eye disc. **(B)** Partial cross-section of a confocal z-stack, with separate fluorescence channels
for **(C)** Histone-RFP, **(D)** Pnt-GFP, and **(E)** Yan antibody. Yellow lines depict nuclear contours
identified by FlyEye Silhouette. **(F)** Manual annotation of R cell types. Image shows a maximum
intensity projection of His-RFP fluorescence across four layers spanning early R cells. R cell
types are readily distinguished by their morphological positions within each ommatidium.
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Figure S2. Pnt-GFP and Yan expression in P cells.
(A) Simultaneous Pnt-GFP (green) and Yan (magenta) expression dynamics in P cells. Lines are
smoothed moving averages across 500 sequential progenitors, shaded regions are bootstrapped
95% confidence intervals for the mean. Arrows indicate the times at which local maxima occur.
Note the peaks of Pnt and Yan take place sequentially in P cells.
(B, C) Expression levels of **(B)** Pnt-GFP and **(C)** Yan in P cells, color-coded in accordance with
the expression level of the complementary transcription factor. In both panels, markers are
arranged such that nuclei with higher levels of the complementary transcription factor are
displayed in front. Lines are smoothed moving averages across 500 sequential P cells.
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901 **Figure S3. Characterization of Pnt-GFP**
902 Adult eyes of flies carrying **(A)** one or **(B)** two copies of the *pnt-gfp* transgene in a *pnt* null
903 mutant background have wildtype retinal patterning.
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905 **Figure S4. Pnt expression, Yan expression and Pnt-to-Yan ratio dynamics**

(A) Measured Pnt-to-Yan ratio dynamics for all annotated cell types. Solid lines are moving averages across 250 and 75 sequential cells for P and R cells, respectively. Shading denotes bootstrapped 95% confidence interval for the moving average. Colors denote cell type. **(B-D)** Pnt and Yan expression dynamics and Pnt-to-Yan ratio dynamics for differentiating **(B^1-B^3)** R8, **(C^1-C^3)** R2/R5, **(D^1-D^3)** R3/R4, and **(E^1-E^3)** R1/R6 cells. Solid lines are smoothed moving averages across 250 and 50 samples for P and R cells, respectively.

Figure S5. Dynamics of expression variability in P, R8, R2/R5, and R1/R6 cells.
Heterogeneities of **(A)** Pnt expression, **(B)** Yan expression, and **(C)** the log2-transformed Pnt-to-Yan ratio are estimated by de-trending fluctuations about a moving average of 250 sequential cells. Lines are moving averages of 250 sequential fluctuations. Shaded regions are bootstrapped 95% confidence intervals for the moving average. Colors denote cell type.

Figure S6. sev>Gal4 drives expression in subsets of P cells.
Projection of *sev-Gal4>UAS-NLS-mCherry* protein expression (red) and DAPI (blue) in apical z-slices containing R cell nuclei and basal z-slices containing progenitor cell nuclei. Anterior left and MF is morphogenetic furrow. **(A)** Expression from a weak *sev-Gal4* driver. **(B)** Expression from a strong *sev-Gal4* driver. Scale bar denotes 20 μm. When expressed from the weak driver, mCherry is predominantly limited to R7, R3, and R4 cells. When expressed from the strong driver, mCherry is also detected in some P cells.

Figure S7. R7 phenotype in *sev>Ras^{V12}* and *sev>Yan^{ACT}*.
Antibody staining of Prospero in 9-10 ommatidia in the equivalent posterior region of the eye disc from **(A)** wildtype, **(B)** *sev>Ras^{V12}*, and **(C)** *sev>Yan^{ACT}* animals. R7 cell is marked based on stereotypical nuclear position. Extra R cells on each side of the R7 are marked as "R" in the *sev>Ras^{V12}* disc.

Figure S8. Yan^{ACT} has little to no effect on Pnt-to-Yan ratio dynamics in R8, R2/R5 or R1/R6 cells but has a moderate effect on R3/R4 cells.
(A-H) Measured Pnt-to-Yan ratio dynamics among differentiating R cells in wildtype (top row) and weak *sev>yan^{ACT}* (bottom row) eye discs. Solid black and yellow lines are moving averages across 250 and 75 sequential cells for P and R7 cells, respectively. Colors denote R cell type.

Figure S9. Yan^{ACT} has no effect on the Pnt-to-Yan ratio in P cells but does affect the ratio in R7 cells.
(A-C) Effects of weak *sev>Yan^{ACT}* expression on **(A)** Pnt-GFP, **(B)** Yan, and **(C)** the Pnt-to-Yan ratio in P cells. Lines are moving averages across 250 sequential cells. Shaded regions are bootstrapped 95% confidence intervals for the mean. Solid lines and grey shading denote wildtype controls. Dashed lines and red shading denote *sev>Yan^{ACT}*. **(D)** Joint distribution of measured Pnt and Yan levels among R7 cells sampled from the region spanning 15 to 20 h of developmental time. The *sev>yan^{ACT}* R7 cells showed higher Yan levels (P<.001, KS 2-sample test), while Pnt levels were indistinguishable from wildtype (P=.4, KS 2-sample test).

Figure S10. A simple model of Yan / Pnt competition for DNA binding sites.
Schematic of a simple two-species competitive binding model (left), alongside theoretical Pnt site occupancy as a function of transcription factor abundance (right). Equivalent binding

affinities are used for illustrative purposes. Color scale reflects overall Pnt site occupancy. A diverging scale was used because all sites are fully saturated at total transcription factor concentrations above 1 nM. Under the range of conditions shown, this implies that Yan occupies all sites left vacant by Pnt. Simultaneous proportional increases in absolute abundance of both species have minimal impact on Pnt occupancy (dashed arrow), while varying ratio confers gradual change in occupancy (solid arrow).

Figure S11. Cooperative DNA-binding sensitizes transcriptional output to the Pnt-to-Yan ratio.

(A) Summary of thermodynamic interactions within one microstate of a cis-regulatory element containing one ETS site and two non-ETS sites. Solid black lines represent individual binding sites. Green and magenta rectangles denote Pnt and Yan molecules. Example thermodynamic potentials of strong ETS-binding, weak non-ETS binding, and polymerization interactions are denoted by αPnt, βYan, and γYan, respectively. For this microstate, $aP(k)=1$ and $aY(k)=2$.

(B) Enumeration of all possible microstates for a cis-regulatory element of length 3 in which only the first site carries the ETS designation. Solid black lines denote binding sites, green and magenta rectangles denote bound Pnt and Yan molecules. The cumulative thermodynamic potentials of each microstate, ΔGk, are listed beside each graphical depiction.

(C) Pnt occupancy of individual binding sites as a function of Pnt-to-Yan ratio in the absence of Yan polymerization. Contours correspond to a vertical path traversed across Figure 6A at a fixed Yan concentration of 50 nM. All binding sites behave similarly.

(D) Relative thermodynamic contributions of binding site affinity versus polymerization to microstate statistical frequencies as a function of Pnt and Yan concentration. For each point in the plane, the influence of site affinity was calculated by weighting the sum of all ETS and non-ETS thermodynamic potentials for each microstate by the statistical frequency of the corresponding microstate. The influence of polymerization was similarly determined. The color scale reflects the relative magnitude of these two summations, normalized by limits of zero and complete polymerization.

(E) Pnt occupancy of individual binding sites as a function of Pnt-to-Yan ratio when Yan polymerizes. Contours correspond to a vertical path traversed across Figure 6B at a fixed Yan concentration of 50 nM. Line colors reflect binding site positions within the cis-regulatory element. Sites at intermediate distances from the strong ETS site (green lines) transition at higher ratios than those nearest and furthest from the strong ETS site (blue and yellow lines).

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

A High RTK input

Yan^ACT expressing P/R cell

B P (N = 3796) R7 (N = 413)

Control

C Sev>Yan^ACT *Yan^ACT expressing cells*

D Concurrent P Young R7

N = 312 N = 98 N = 362 N = 20

Control Sev>Yan^ACT

E Control

R8, R2/R5, R3/R4, R1/R6, R7

Sev>Yan^ACT

R8, R2/R5, R3/R4, R1/R6, R7

Figure 6

Table S1

Table S1. Accuracy of cell-type identification

Cell Type Scored	Cell Type Marker	Sample Size (n)	% Correct Type Assignment
Progenitors	Elav (-)	462	99.8
All mature Rs	Elav (+)	258	99.2
R8	Sens	106	97.2
R2/R5	Rough	162	99.4
R3/R4	Rough	142	100.0
R7	Pros	104	99.0

Figure S1

Figure S2

Figure S3

A — 1x *pnt-gfp*

B — 2x *pnt-gfp*

Figure S4

Figure S5

Figure S6

A   sev-Gal4 (weak)>UAS-NLS-mCherry

Apical (R cells)   Basal (P cells)

mCherry
DAPI

MF   MF

B   sev-Gal4 (strong)>UAS-NLS-mCherry

Apical (R cells)   Basal (P cells)

mCherry
DAPI

MF   MF

A **wildtype**

B **sev-Ras^V12**

C **sev-Yan^ACT**

Figure S8

A

Pnt (a.u.)

1   2

Control
Sev>Yan^ACT

Time (h)

B

Yan (a.u.)

1   2

Conntrol
Sev>Yan^ACT

Time (h)

C

log$_2$ Pnt:Yan ratio

1   2

Control
Sev>Yan^ACT

Time (h)

D

Pnt (a.u.)

○ Control R7 cells
○ Sev>Yan^ACT R7 cells

Yan (a.u.)

Figure S10

Figure S11