Predicting focal colors

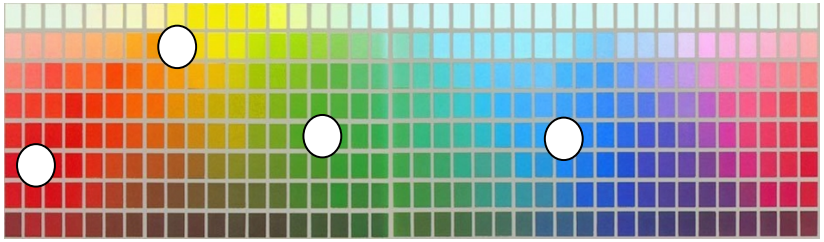
with a rational model of representativeness

Joshua T. Abbott
Terry Regier
Thomas L. Griffiths

Q:

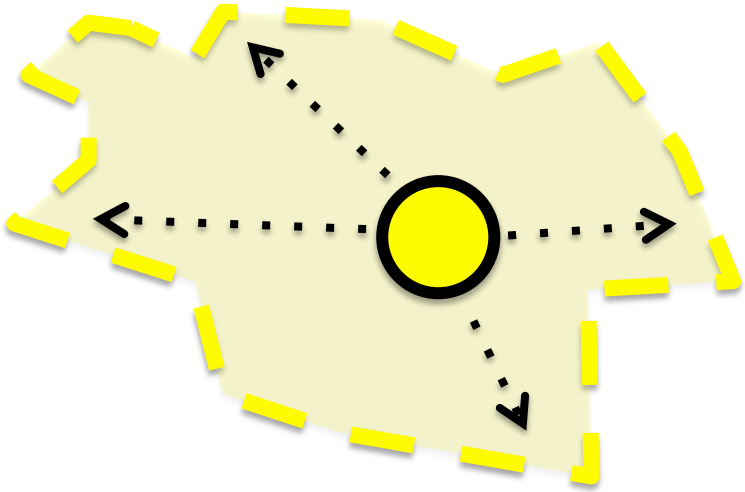
Does color naming reflect universals of cognition, or culturally varying linguistic convention?

Universalist

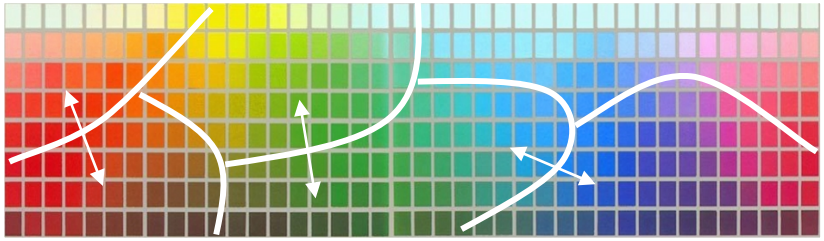


Categories organized around 6 universal foci: black, white, red, green, yellow, blue.

(Berlin & Kay, 1969; Heider, 1972)

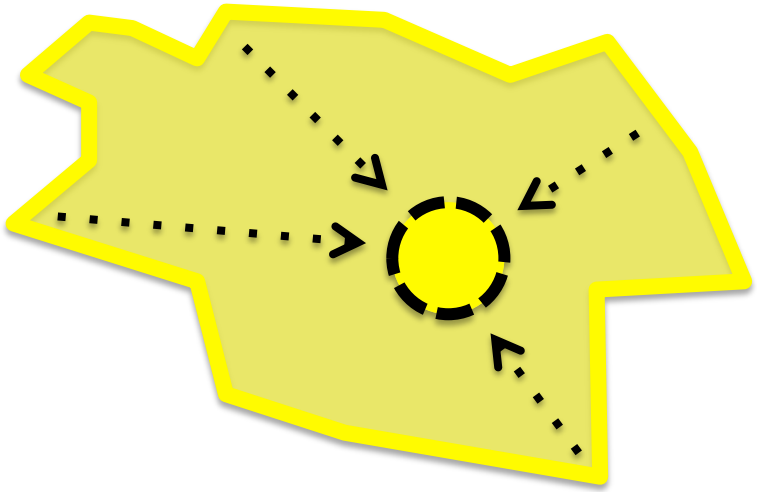


Relativist

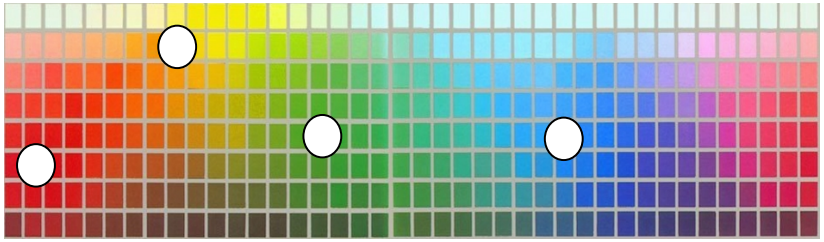


No universal foci: categories organized at *boundaries* by linguistic convention.

(Roberson, Davies, & Davidoff, 2000)

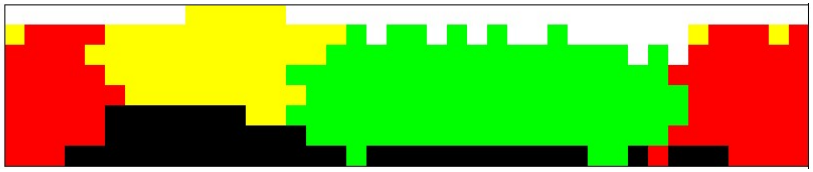


Universalist

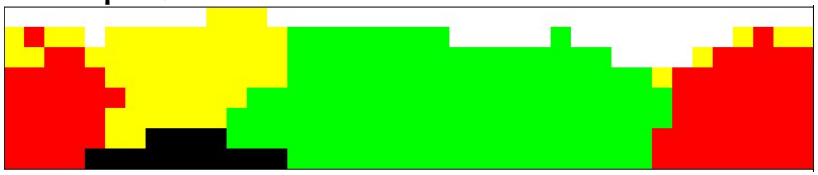


Berinmo, Papua New Guinea

Sirionó, Bolivia



Jicaque, Honduras



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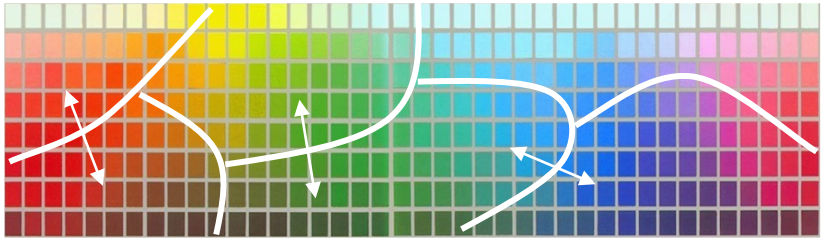
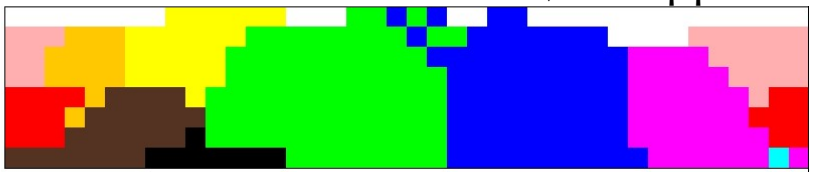
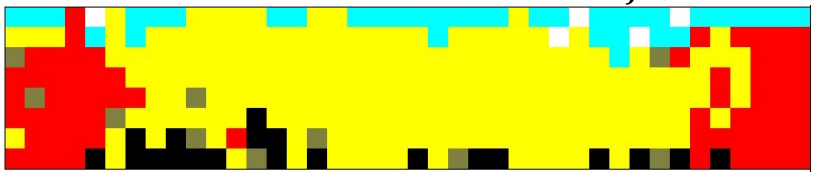


Wobé, Ivory Coast

Chavacano, Philippines



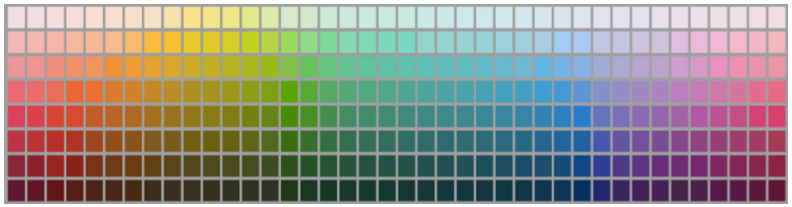
Karajá, Brazil

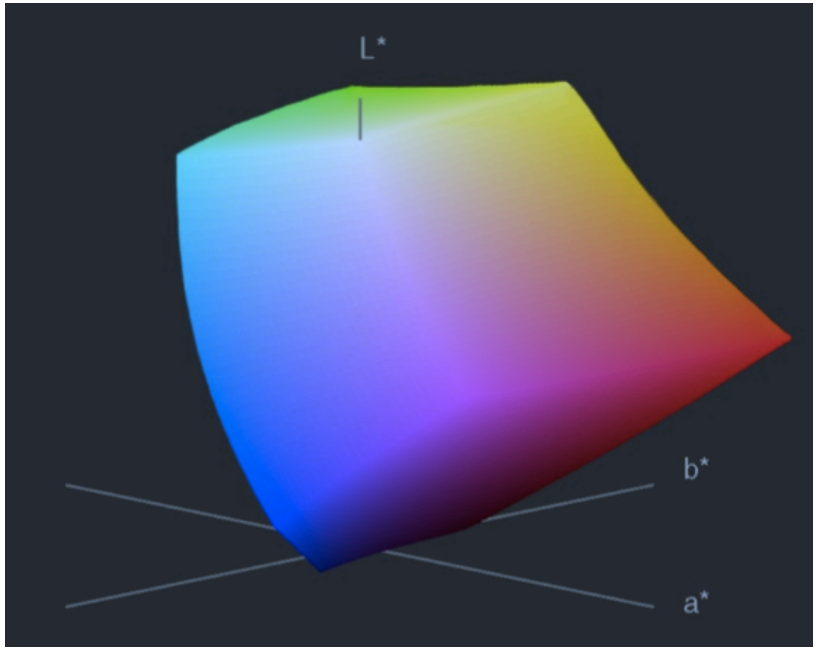


Color naming may reflect *near-optimal* partitions of perceptual color space

(Jameson & D'Andrade, 1997; cf. Liljencrants & Lindblom, 1972 on vowel systems)

Perceptual color space is *irregularly shaped*.





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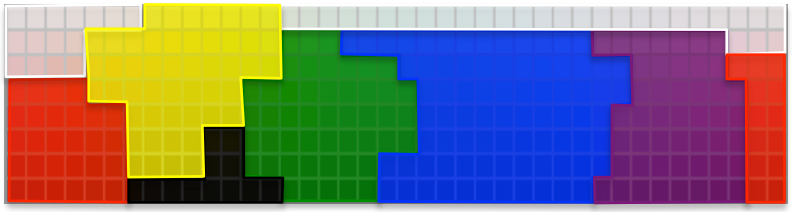
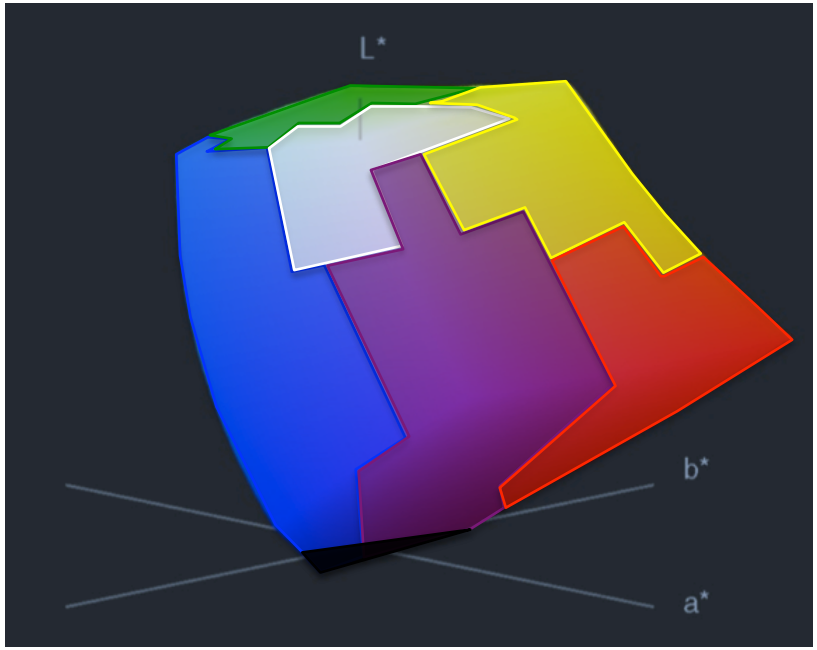




Color naming may reflect *near-optimal* partitions of perceptual color space

(Regier, Kay, & Khetarpal, 2007)

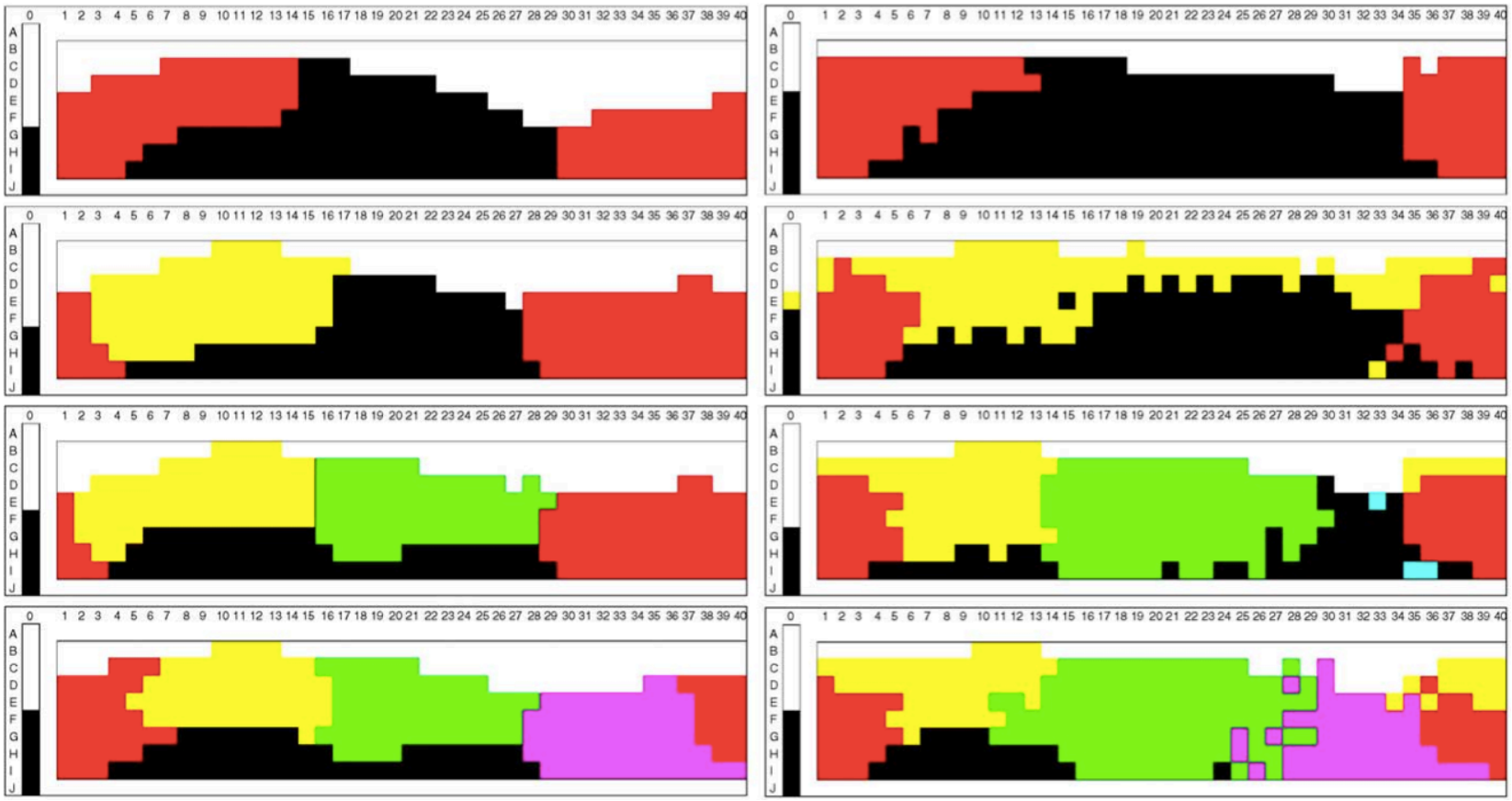
theory **data**

3-term

4-term

5-term

6-term



Explains: Universal tendencies in the *boundaries* of color categories

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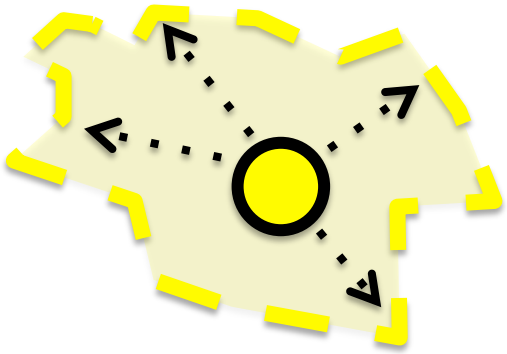
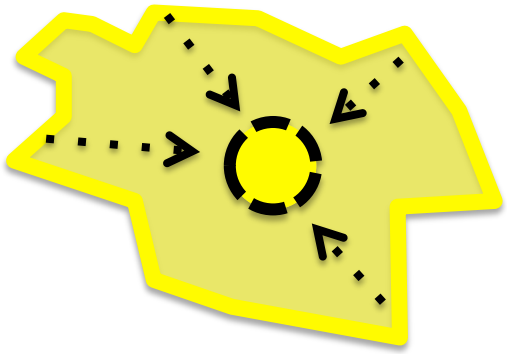
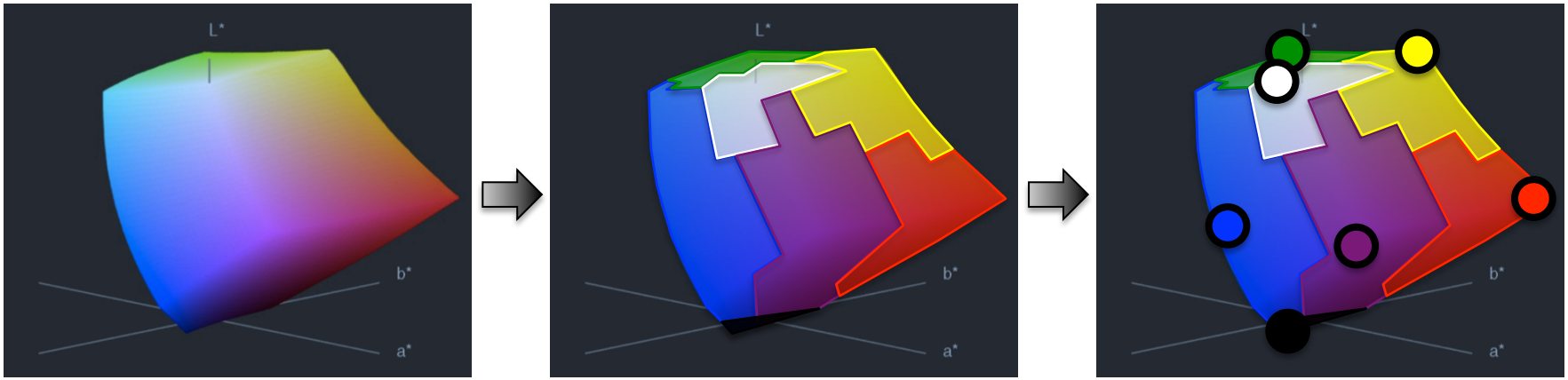
Left unexplained: Focal colors, which lie at the heart of the debate.





Claim: Foci may be derived from boundaries, as optimal examples of categories



How do we test this claim ?

If our claim is true, we should be able to predict foci from boundaries *across* the world's languages

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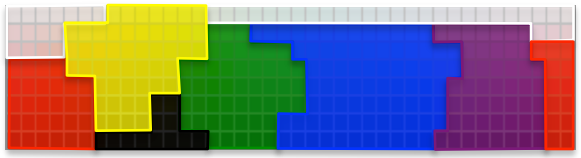
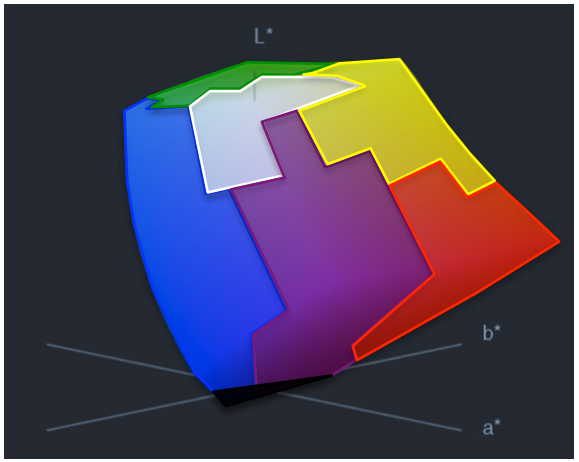
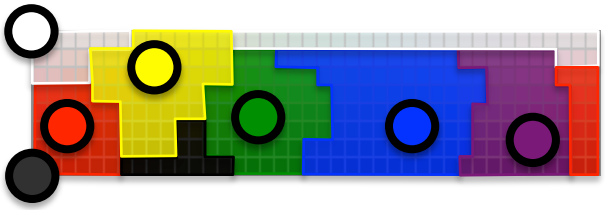
Naming Data

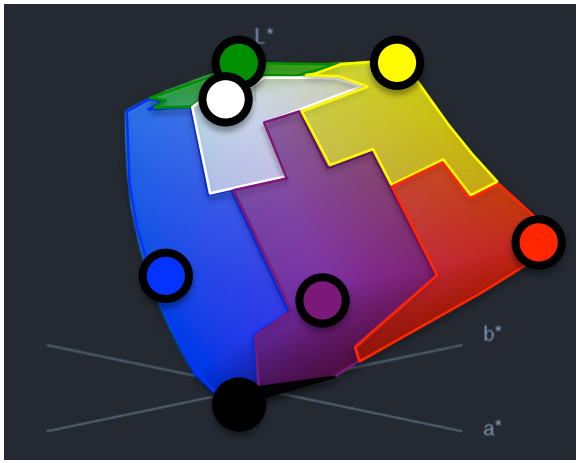




Model

Focus Data





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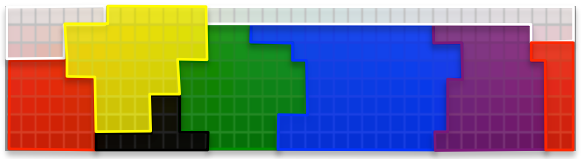

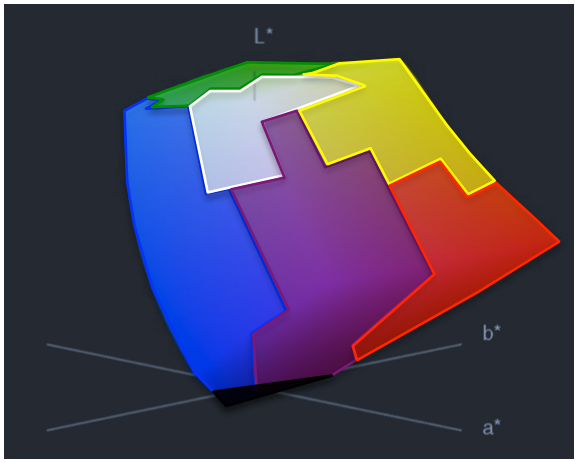

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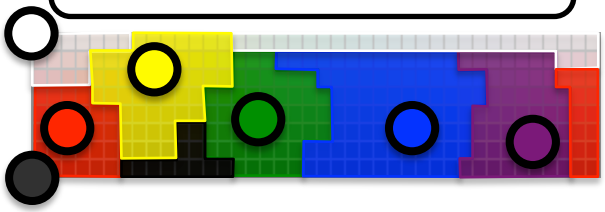
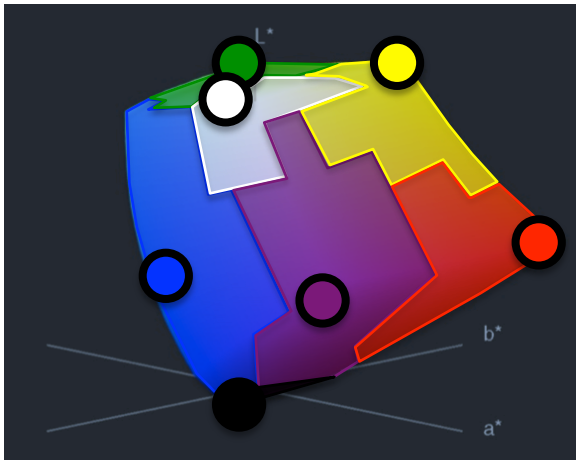
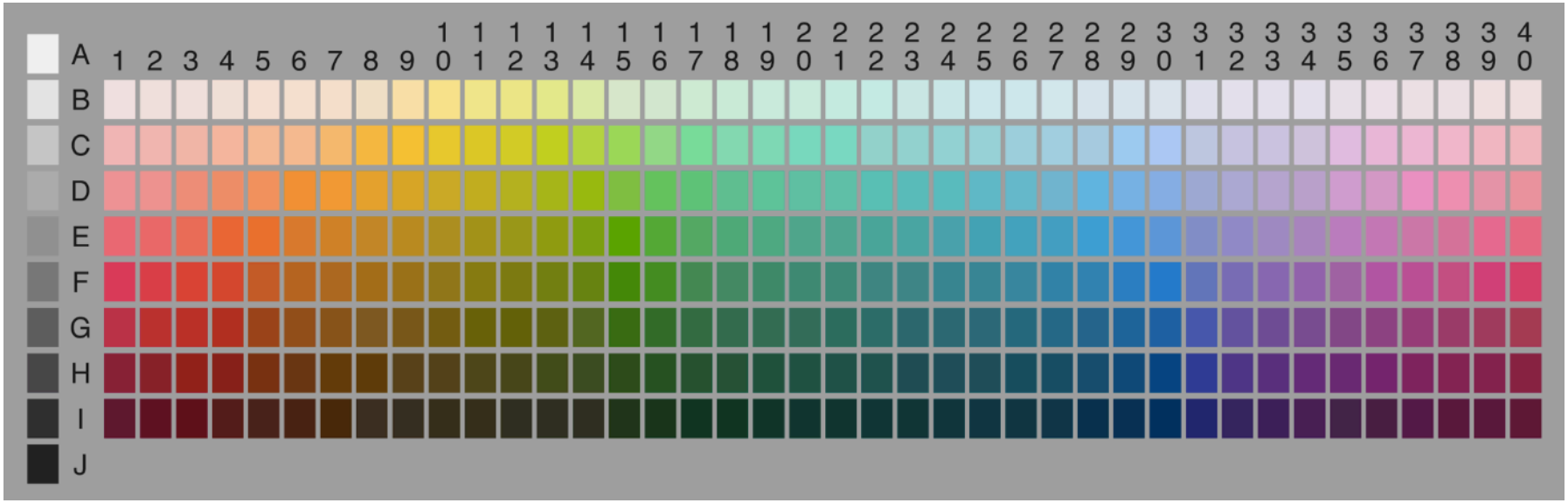
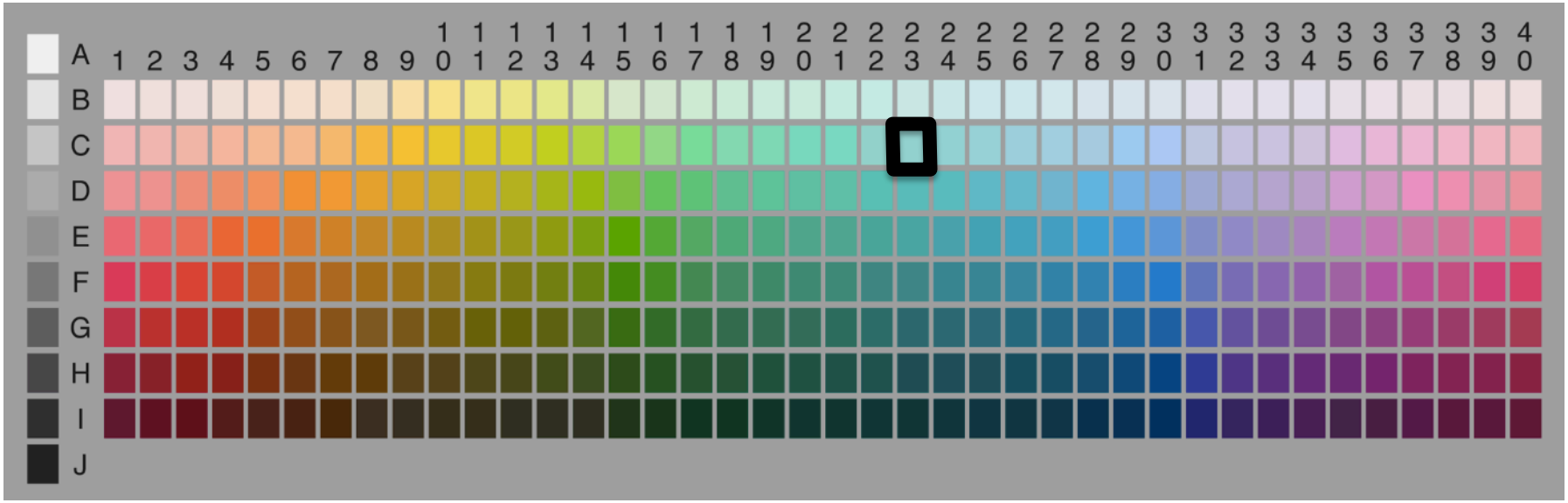




World Color Survey



(Cook, Kay, & Regier, 2005)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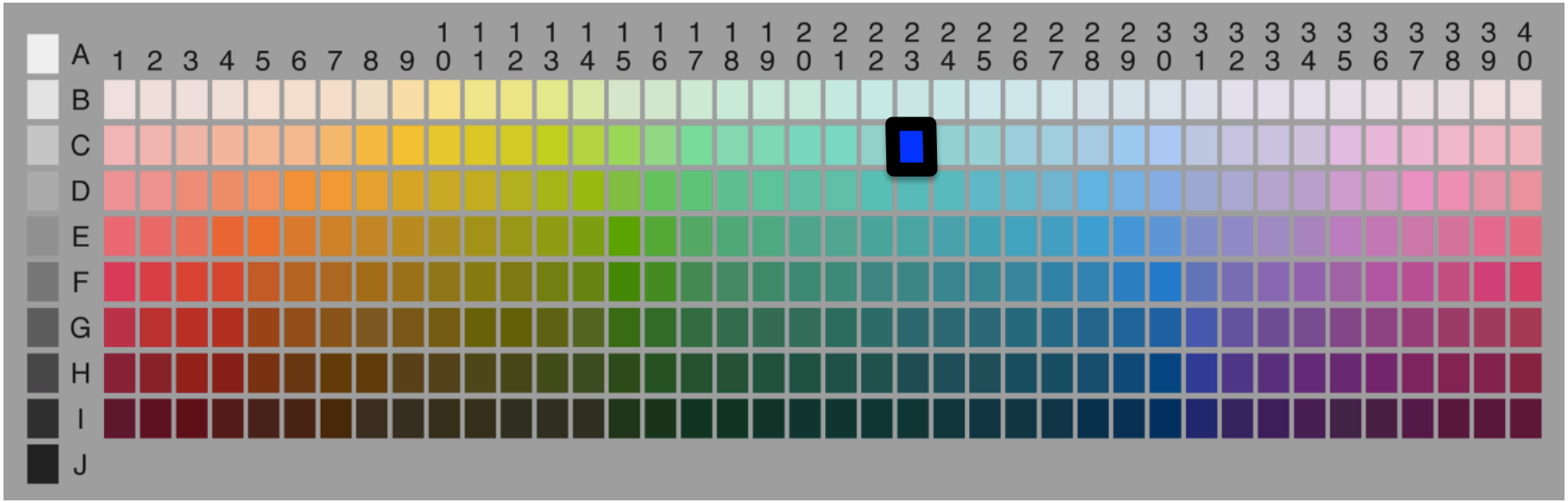
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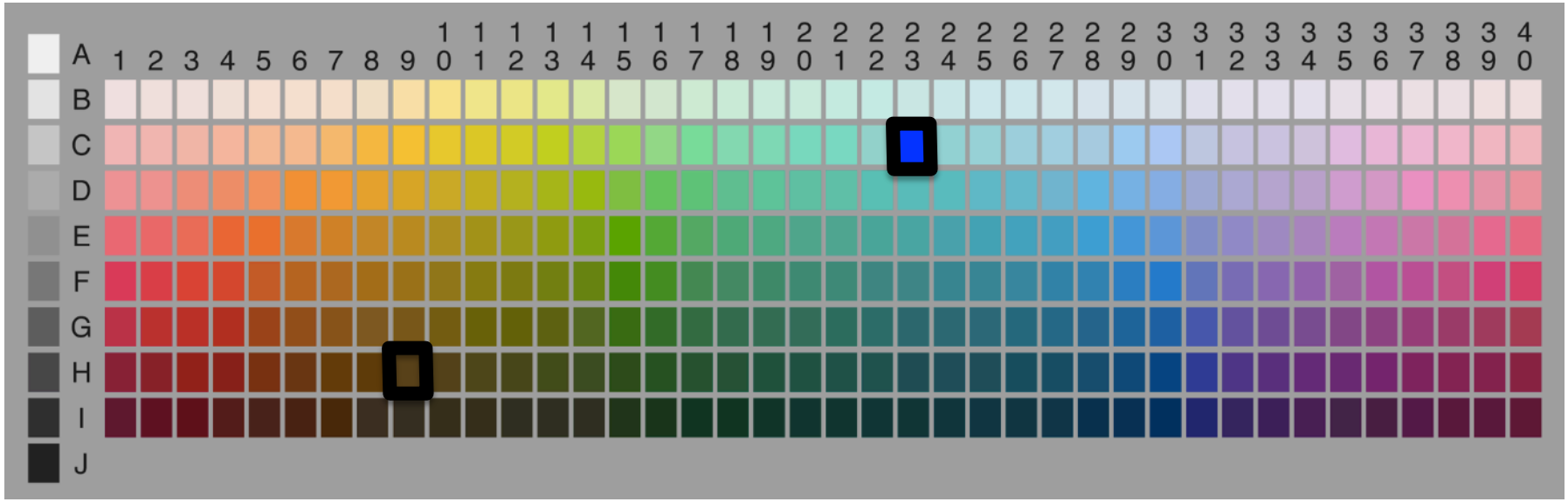
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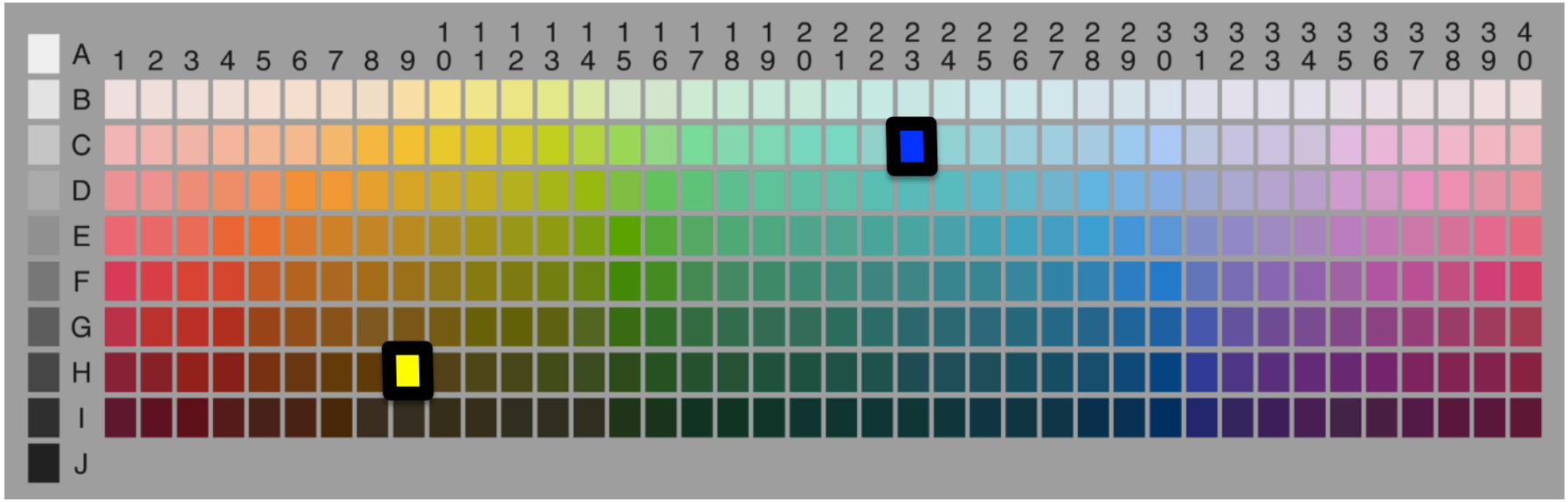
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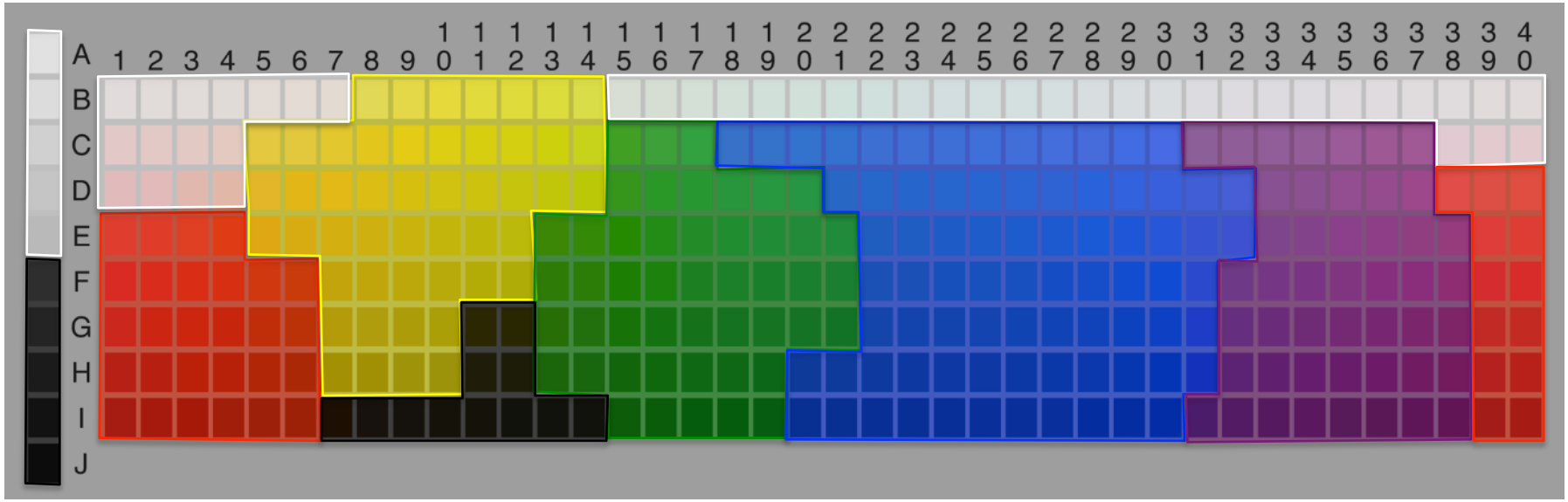
Naming Data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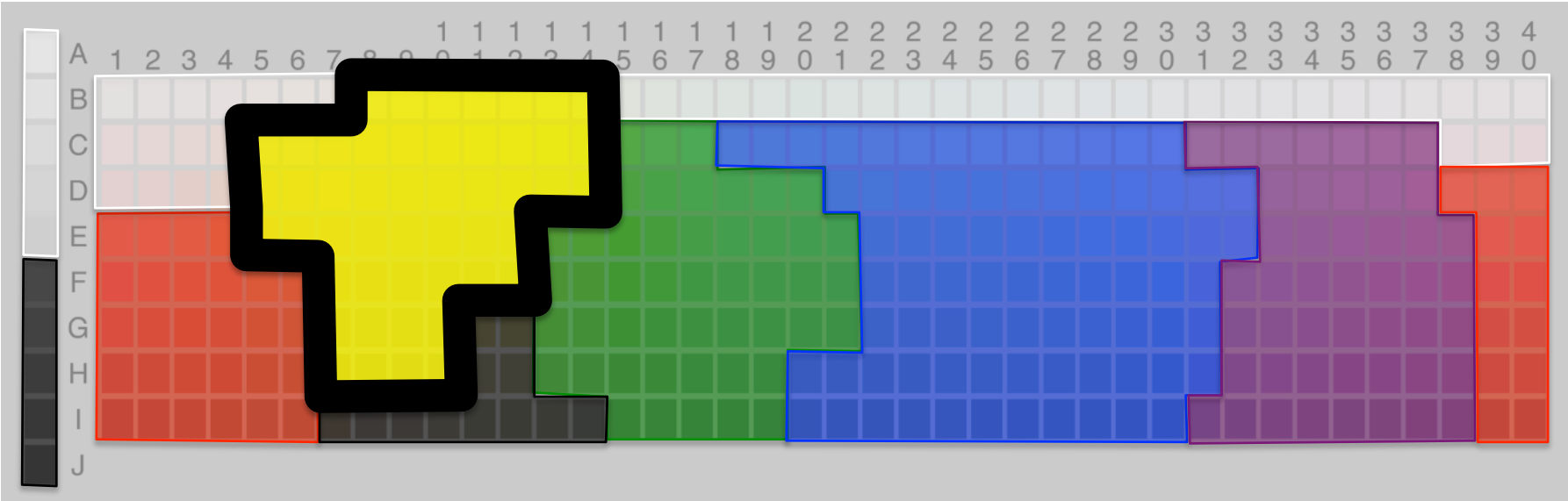
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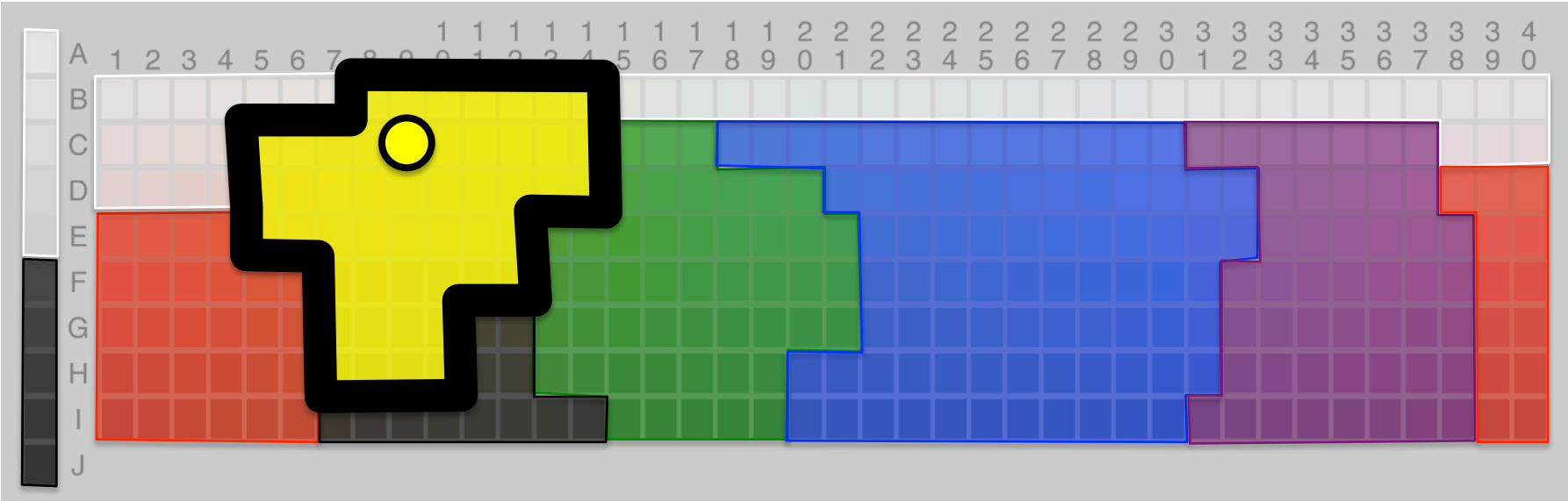
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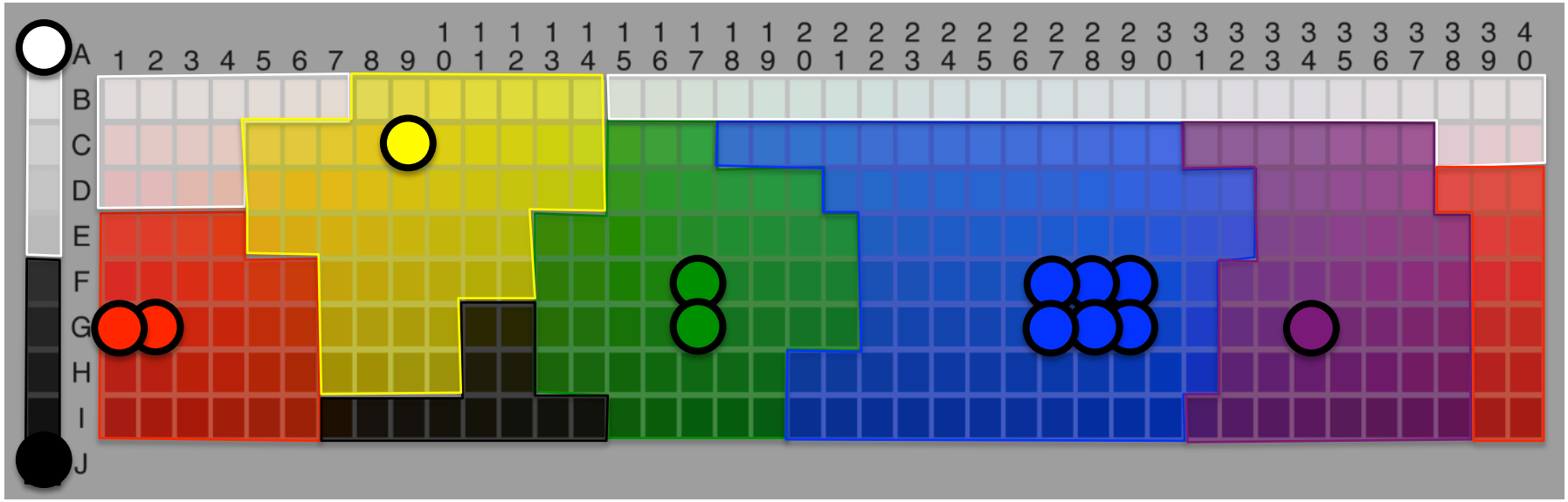
Focus Data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How do we test this claim ?

If our claim is true, we should be able to predict foci from boundaries *across* the world's languages

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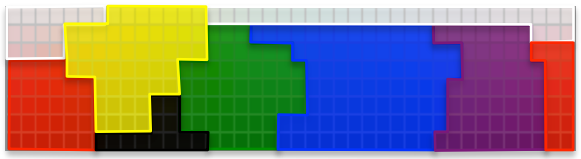

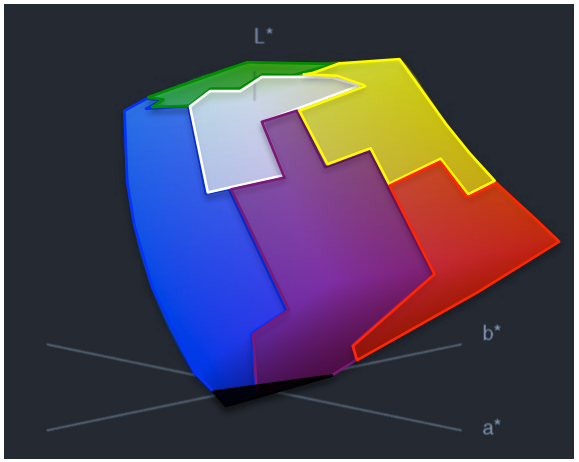

Model

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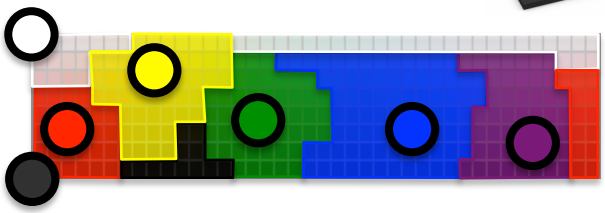

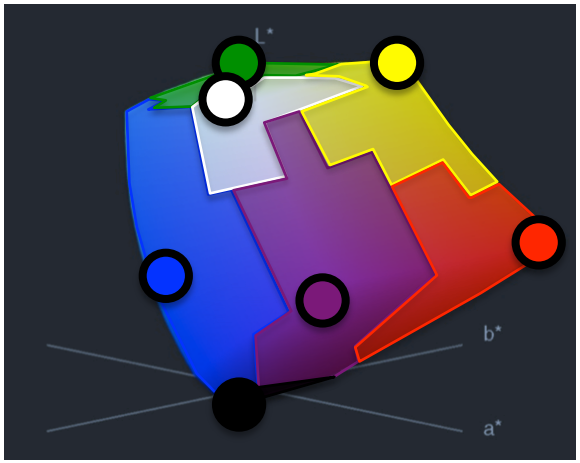

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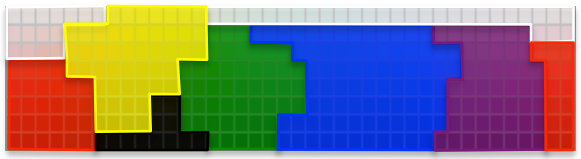

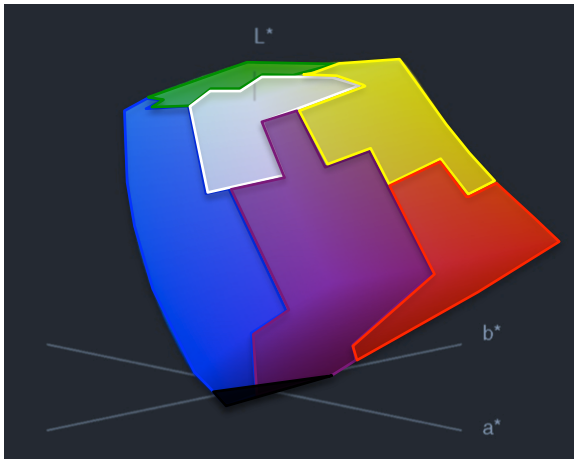

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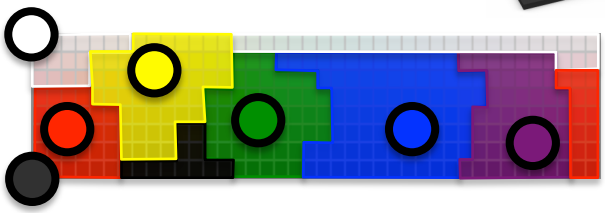
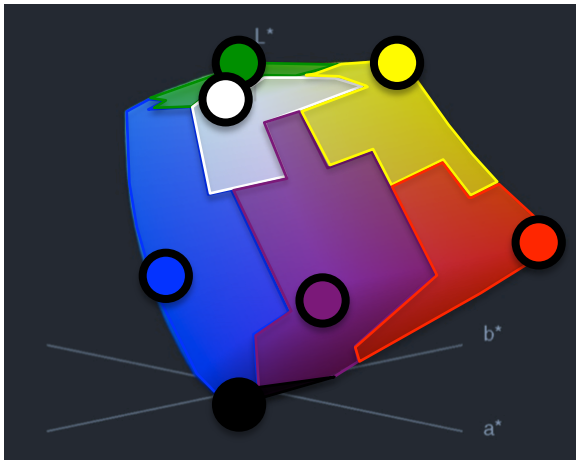
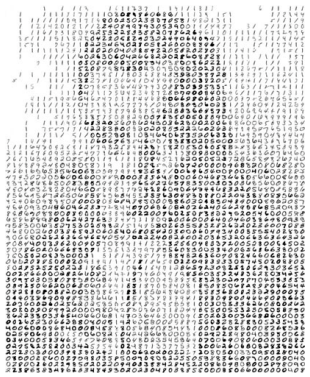


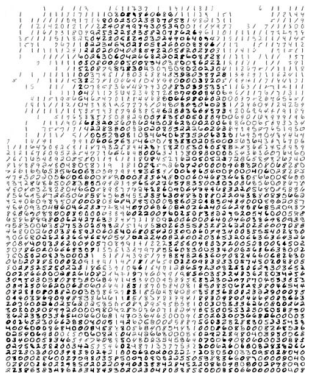




$$R(d,h) = \log \frac{p(d \mid h)}{\sum_{h' \neq h} p(d \mid h')p(h')}$$

h: hypothesis
d: data

(Tenenbaum and Griffiths, 2001)



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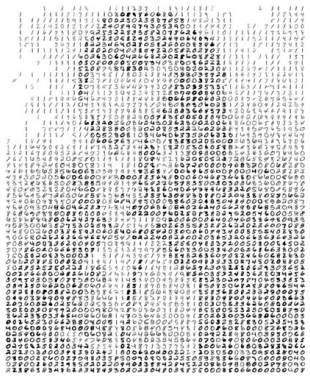
h: color category
d: individual color chip



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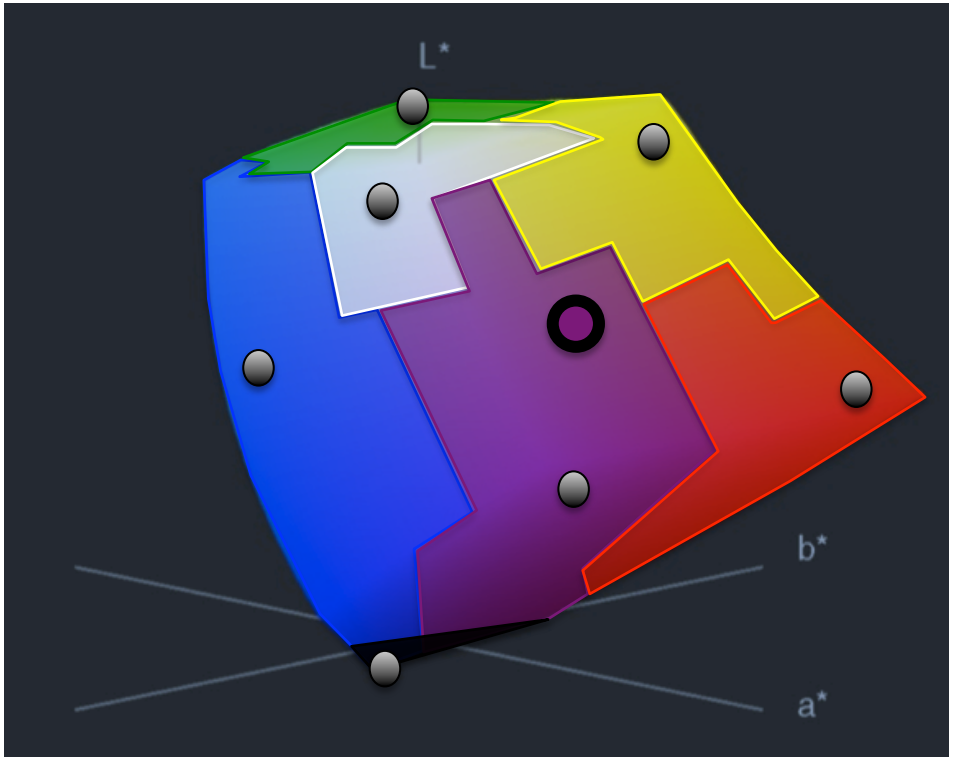

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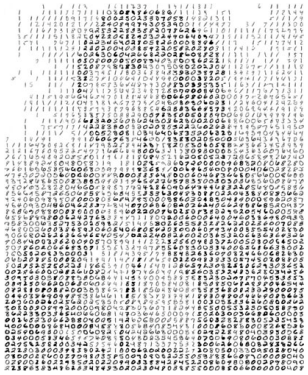

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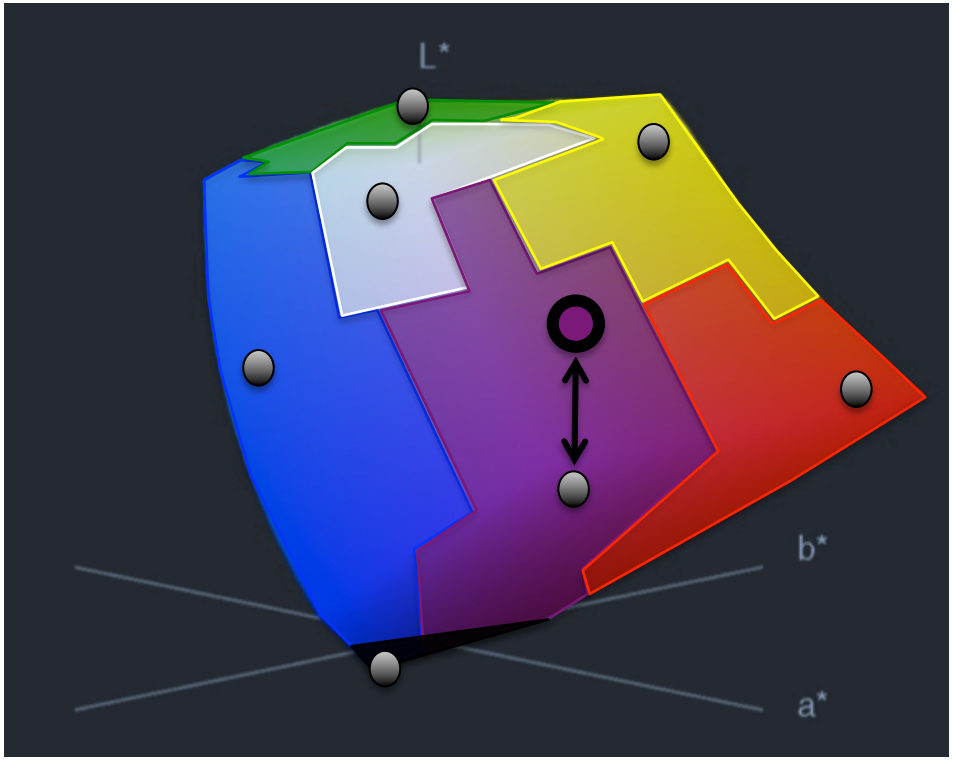

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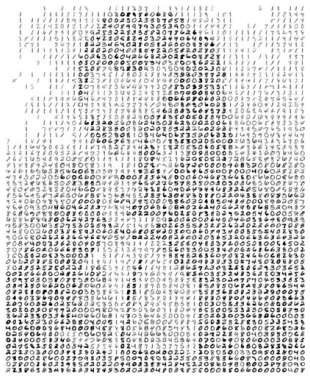

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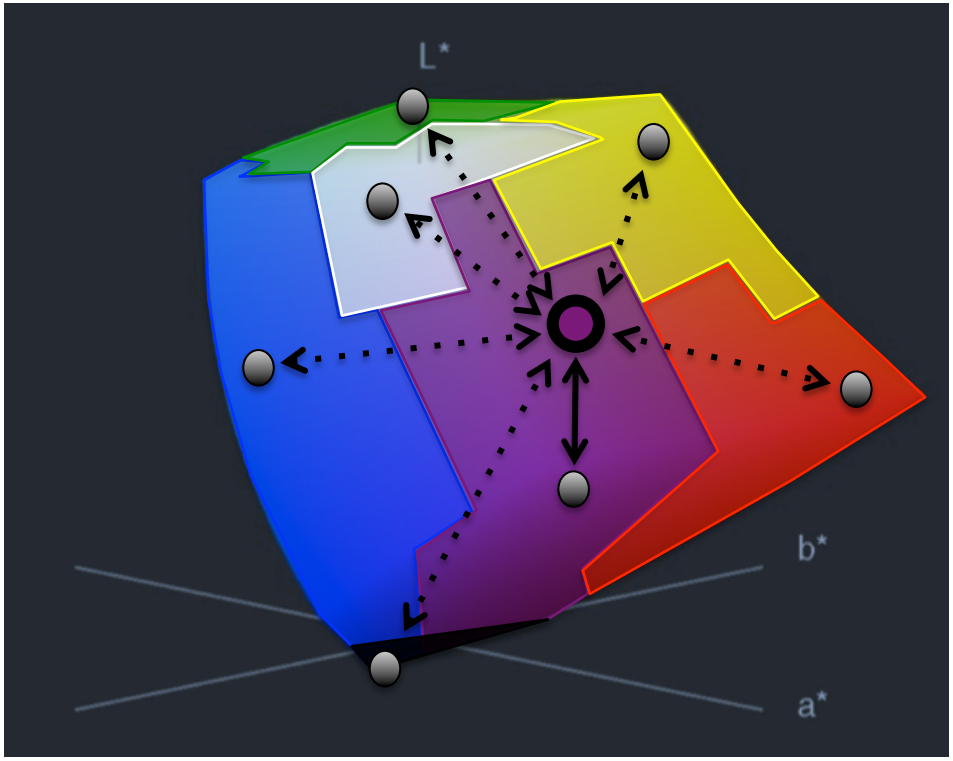

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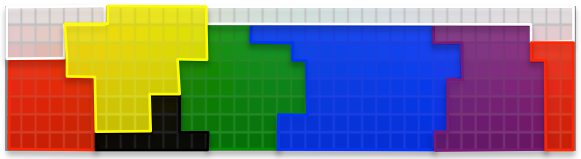
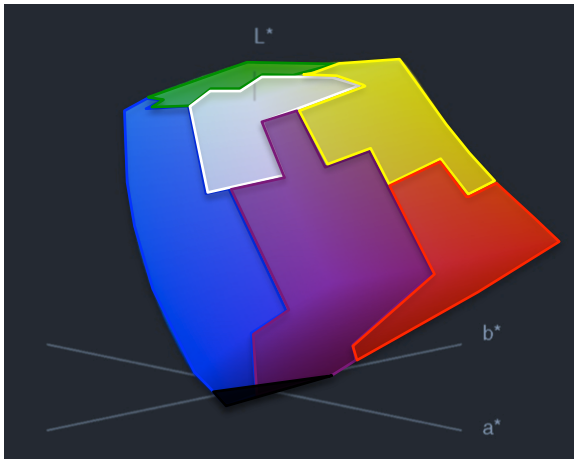
If our claim is true, we should be able to predict foci from boundaries *across* the world's languages

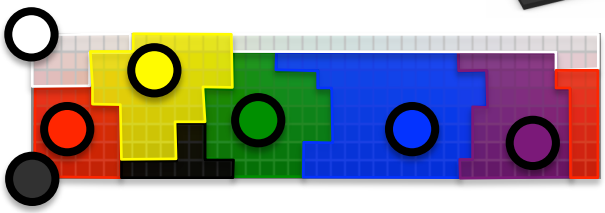
Naming Data

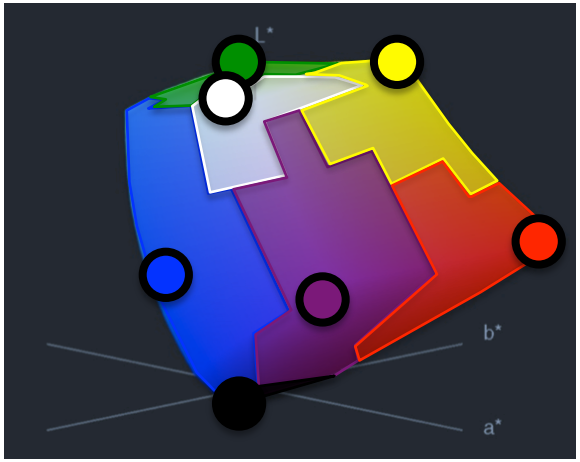


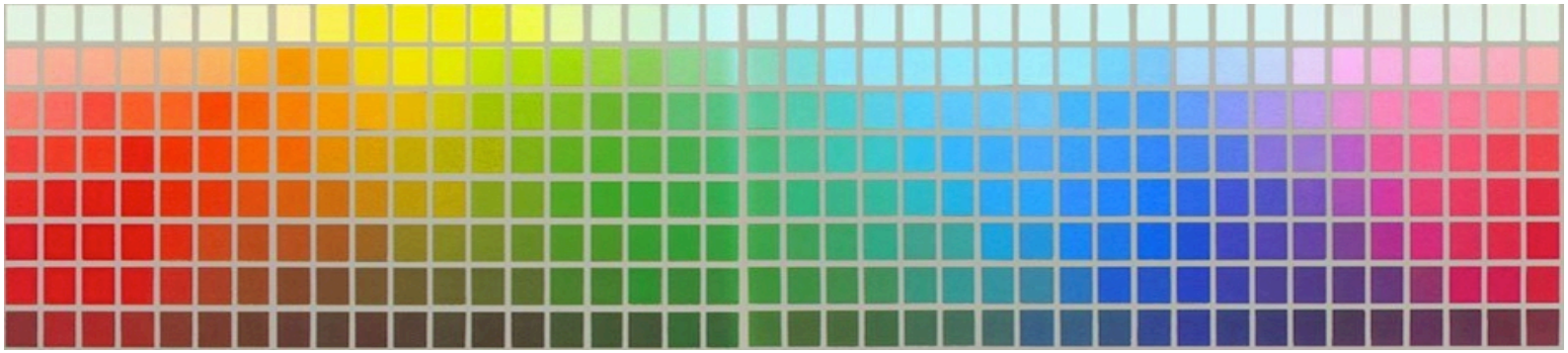


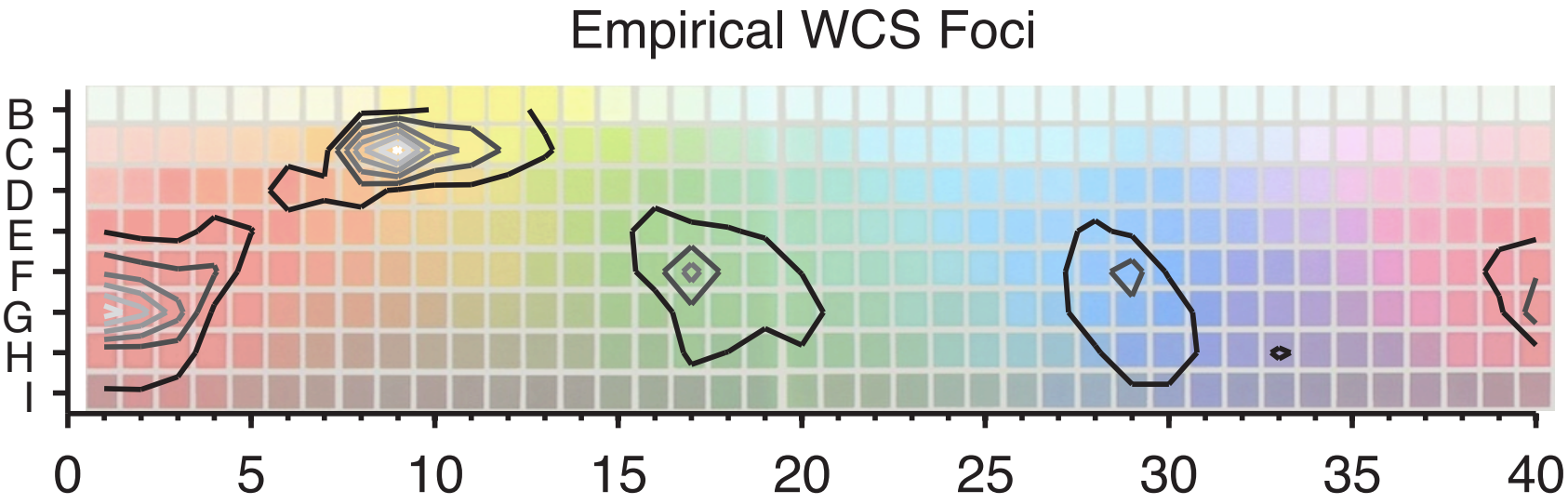
Model

Focus Data








Empirical WCS Foci
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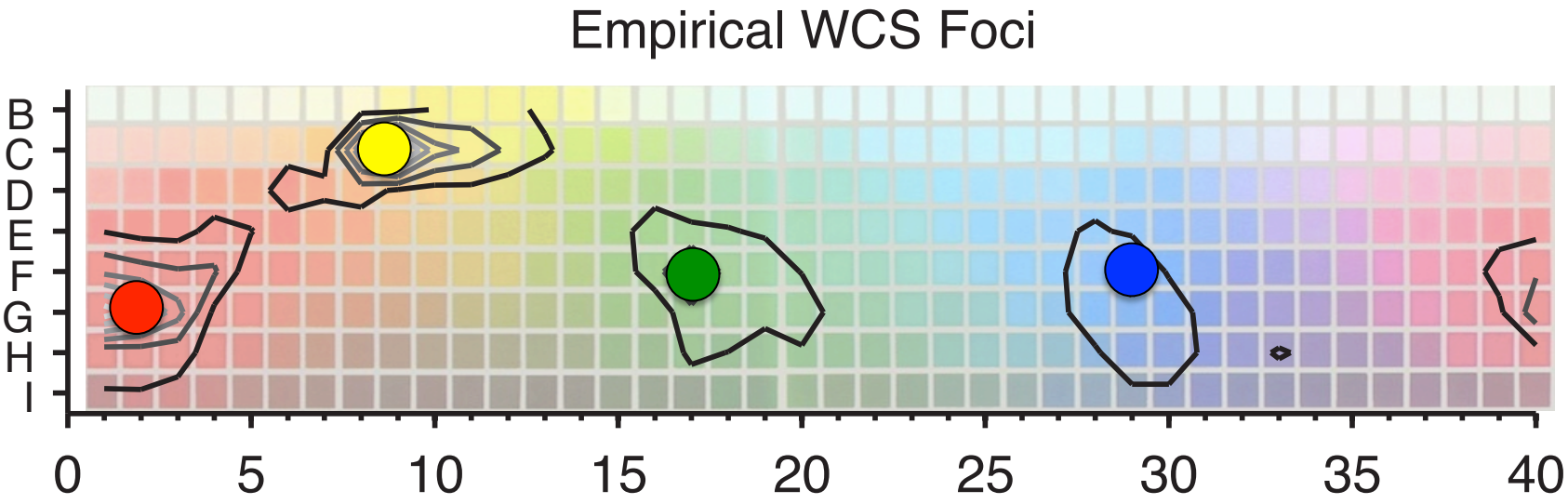
Empirical WCS Foci
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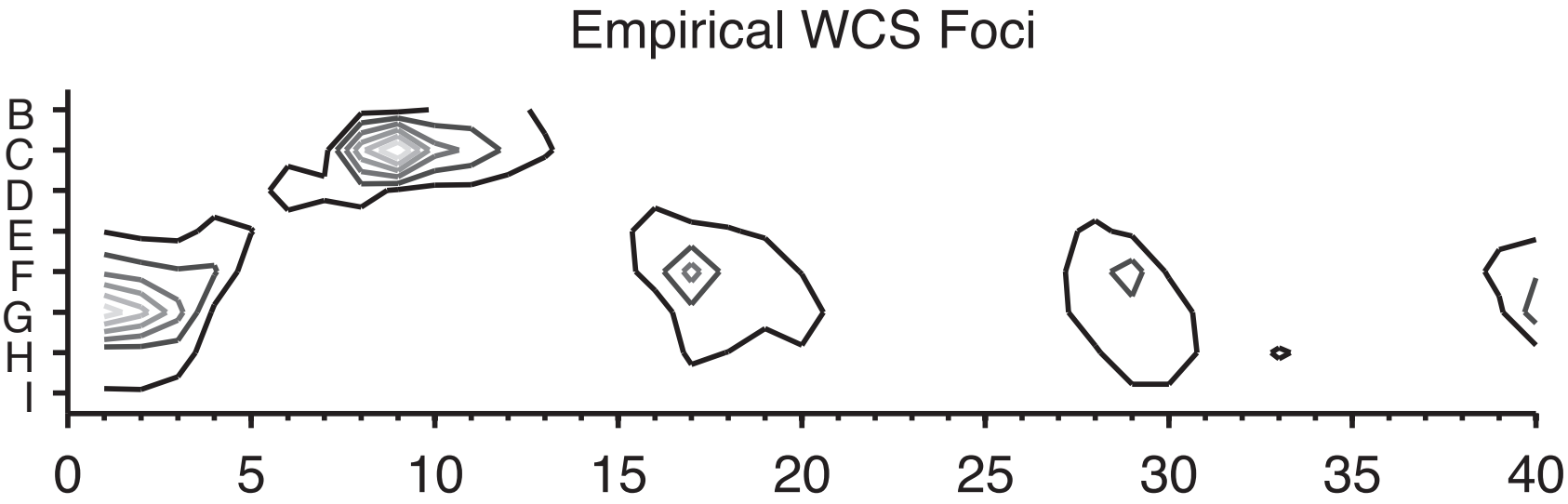
Empirical WCS Foci
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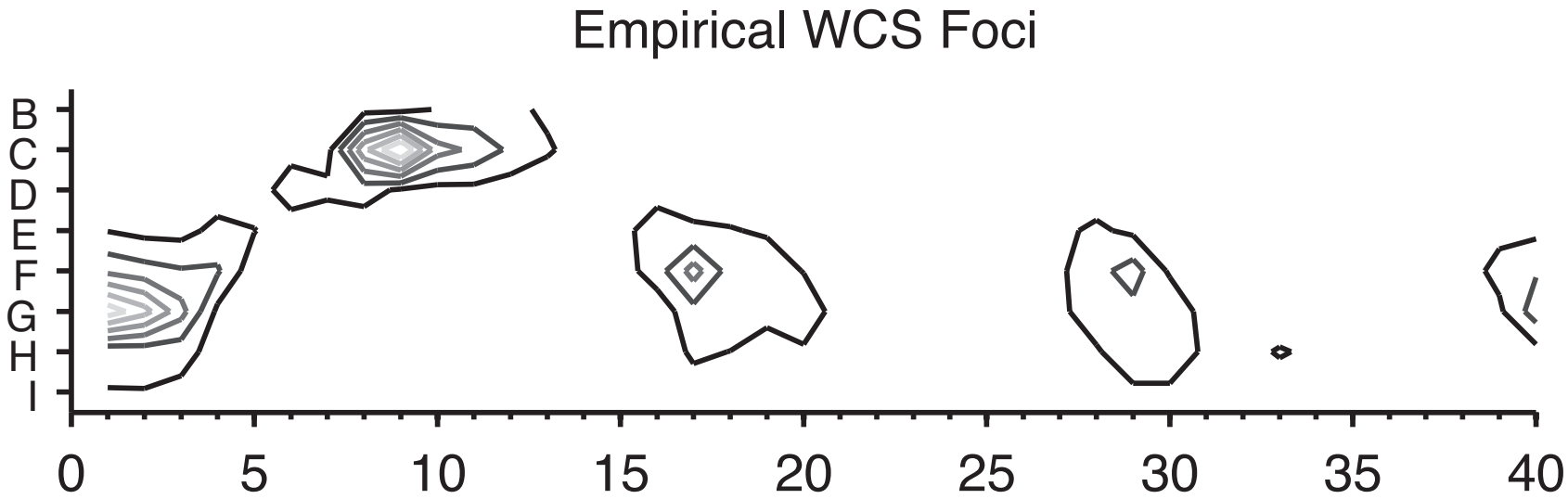
Empirical WCS Foci
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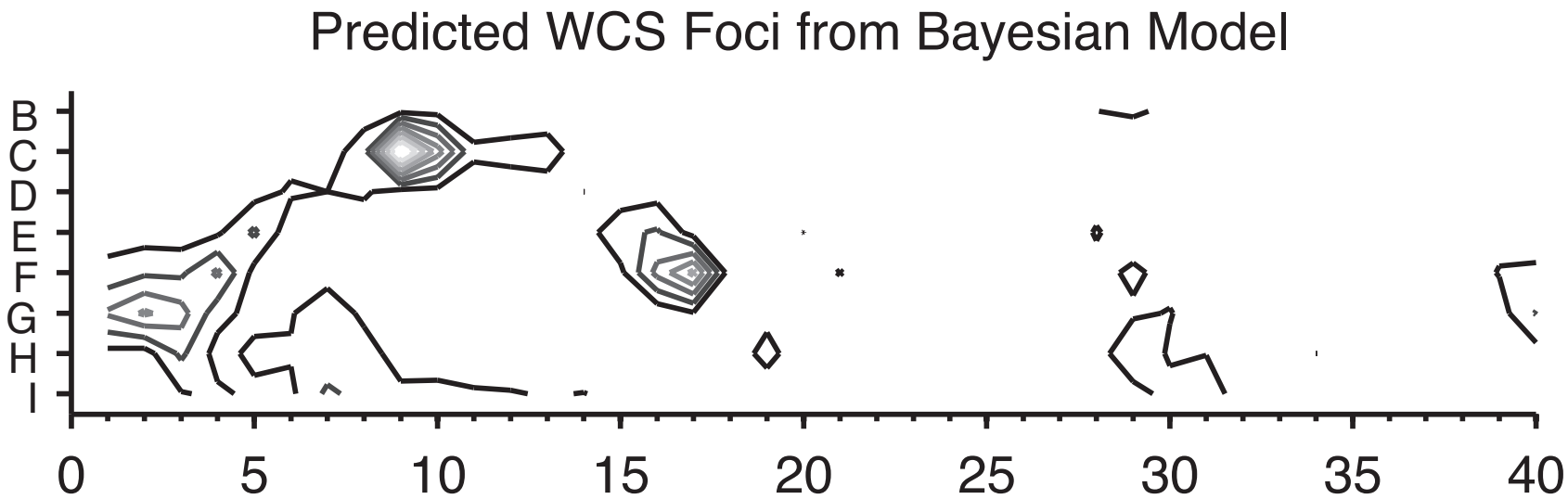
Predicted WCS Foci from Bayesian Model
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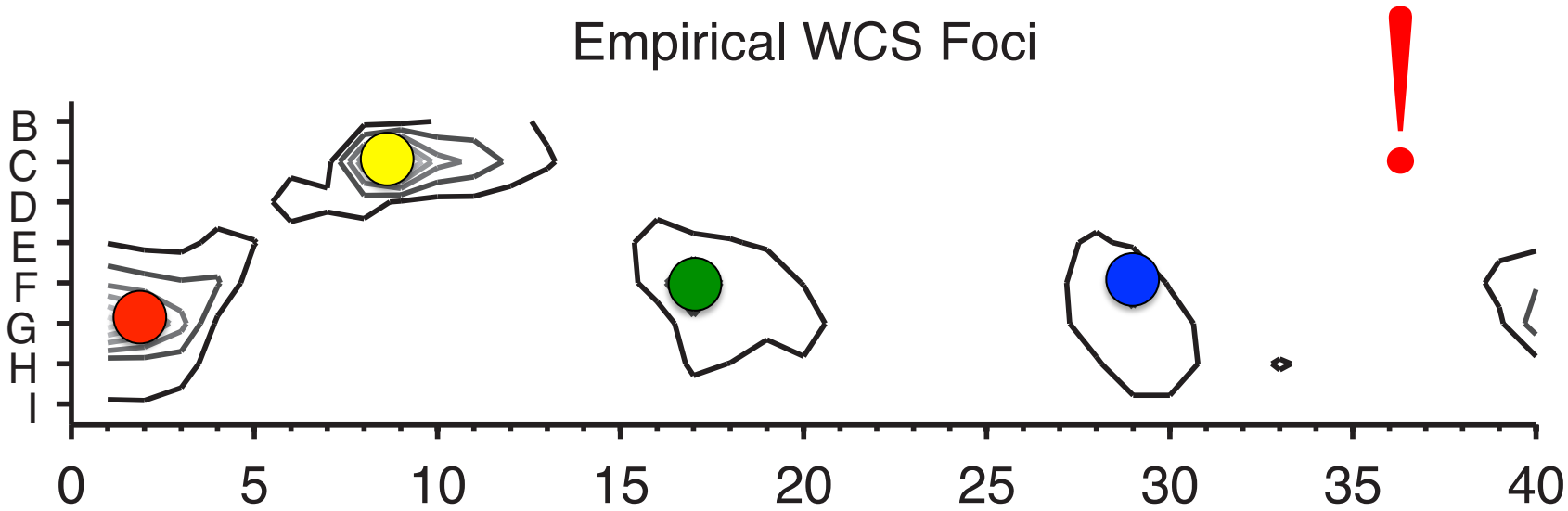
Empirical WCS Foci
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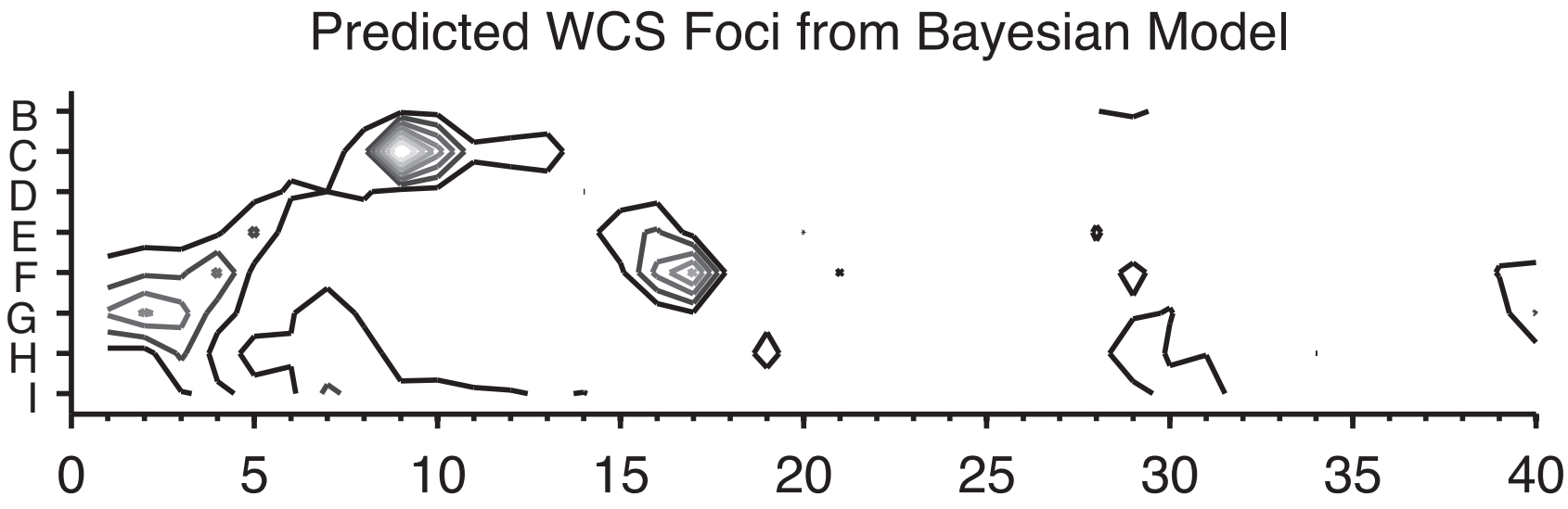
Predicted WCS Foci from Bayesian Model
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How do we discriminate?

How do we discriminate?

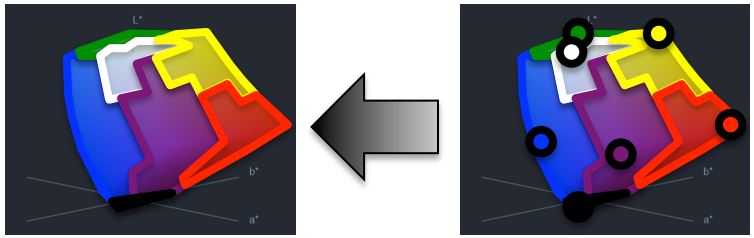
Answer: Languages with unusual boundaries

How do we discriminate?

Answer: Languages with unusual boundaries

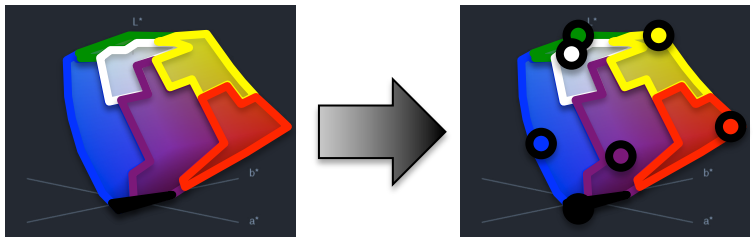
Predictions

Universal Foci:



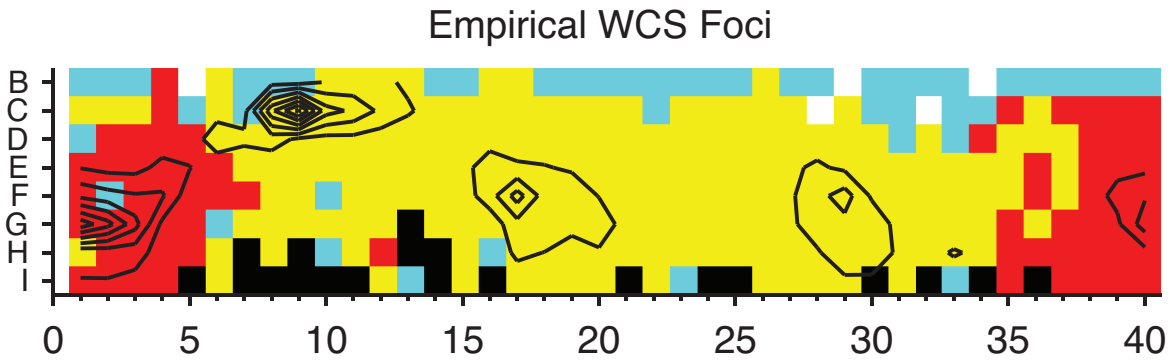
foci fall in canonical positions

Derived Foci:



foci follow boundaries

Karajá


Empirical WCS Foci
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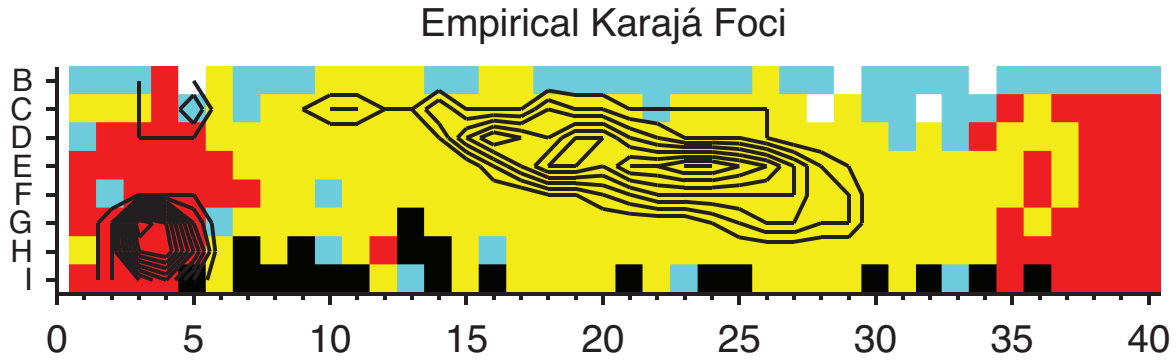
Empirical Karajá Foci
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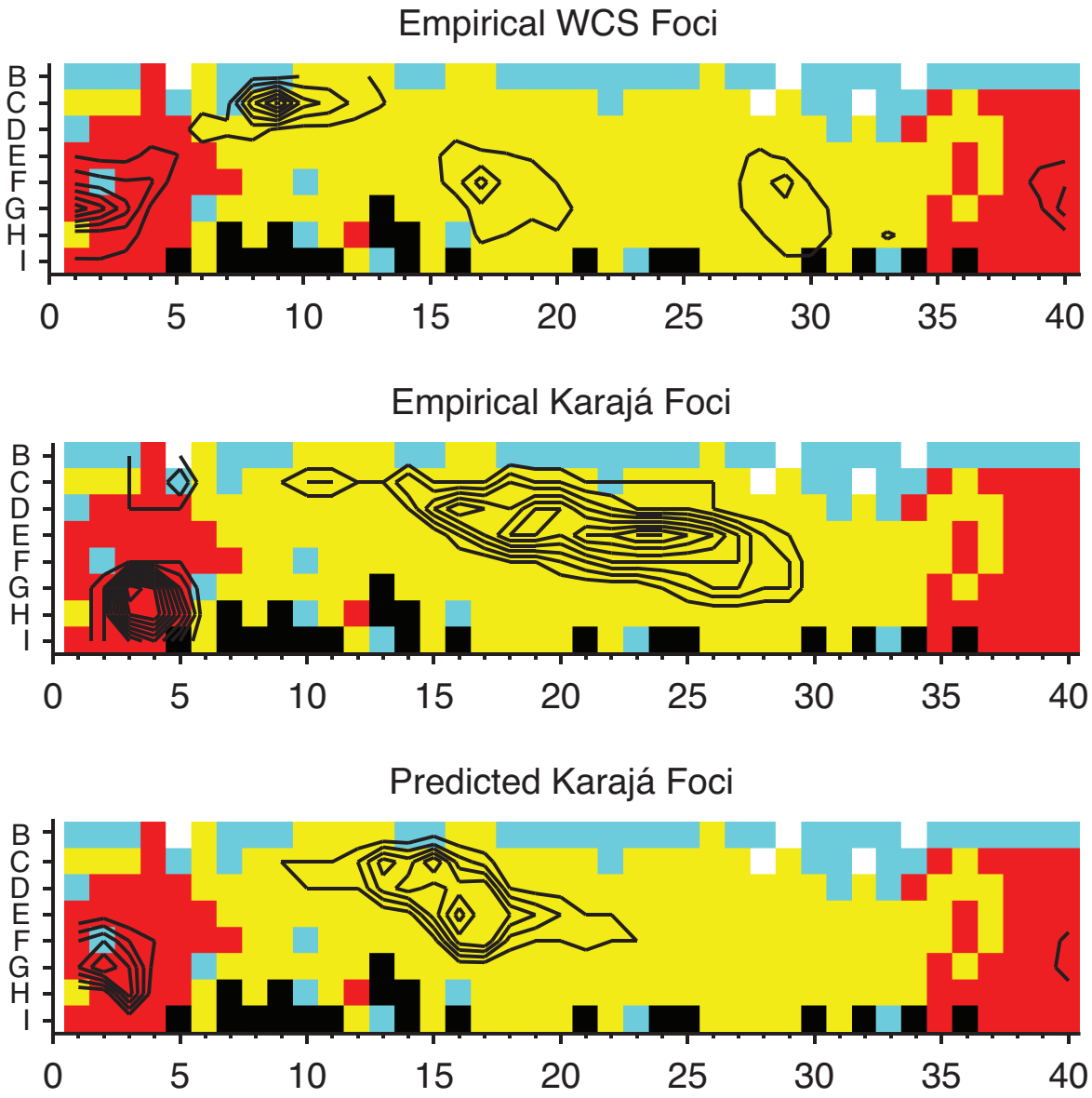
Empirical WCS Foci
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Empirical Karajá Foci
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Predicted Karajá Foci
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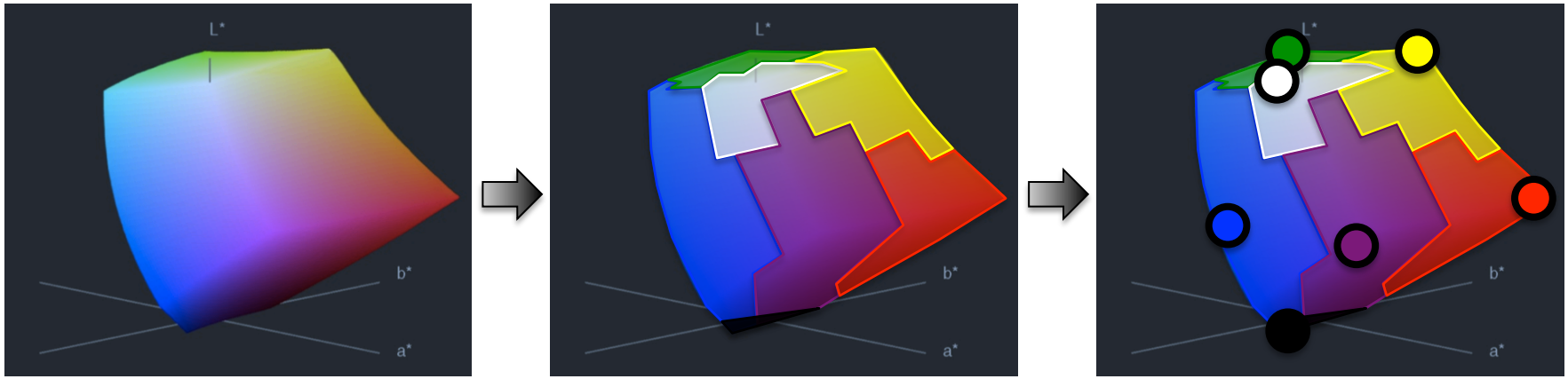
Conclusions

foci may not be the source of universals

instead, foci may be optimally representative members of categories that are defined at their boundaries

the boundaries themselves result from near-optimally informative partitions of color space

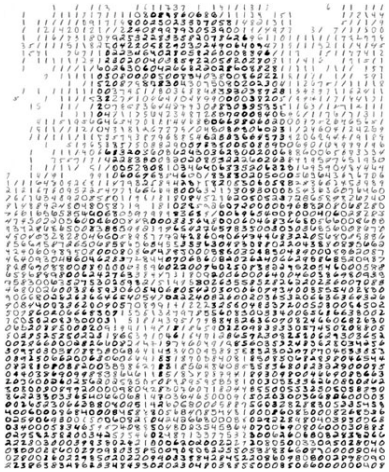


Questions?

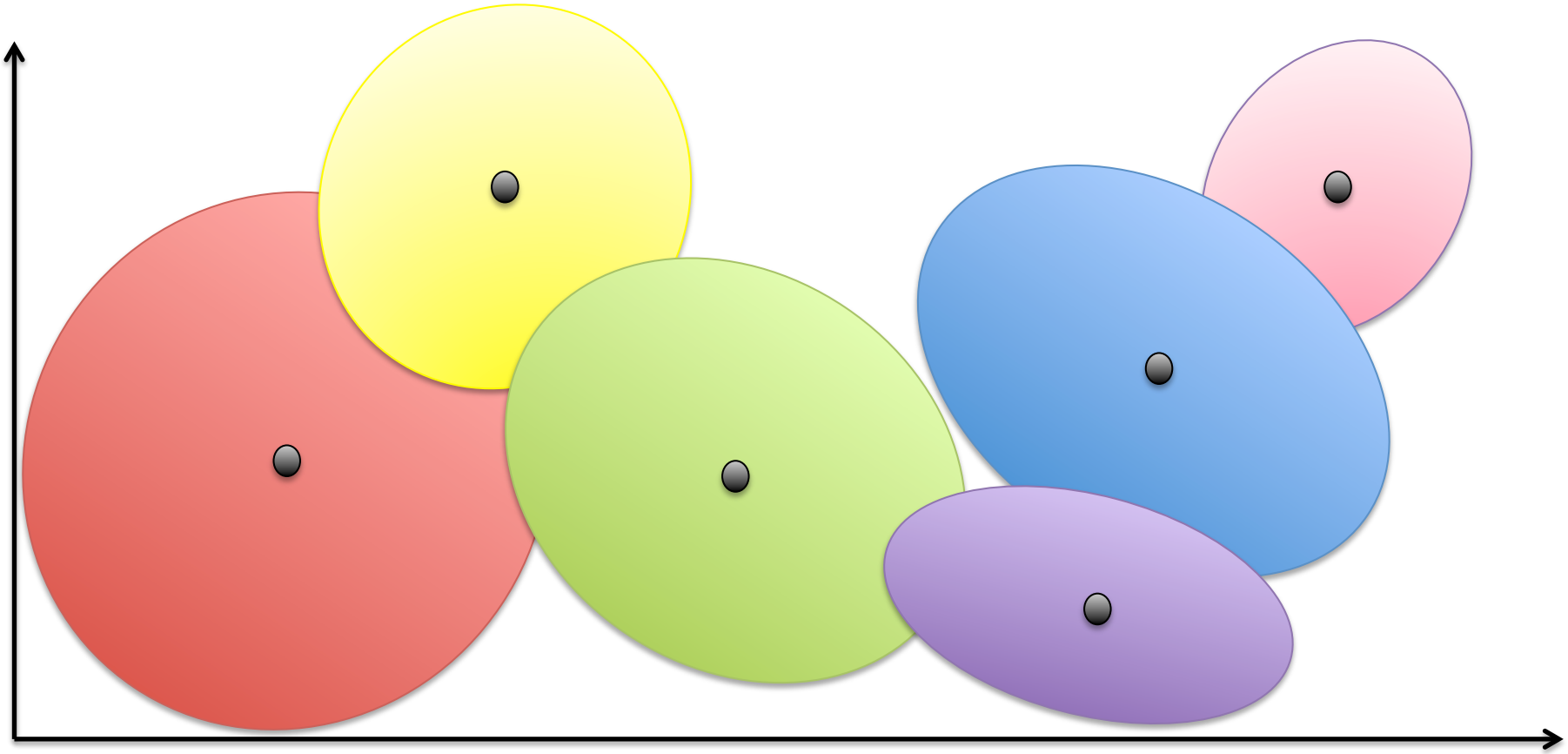
joshua.abbott@berkeley.edu

EXTRAS

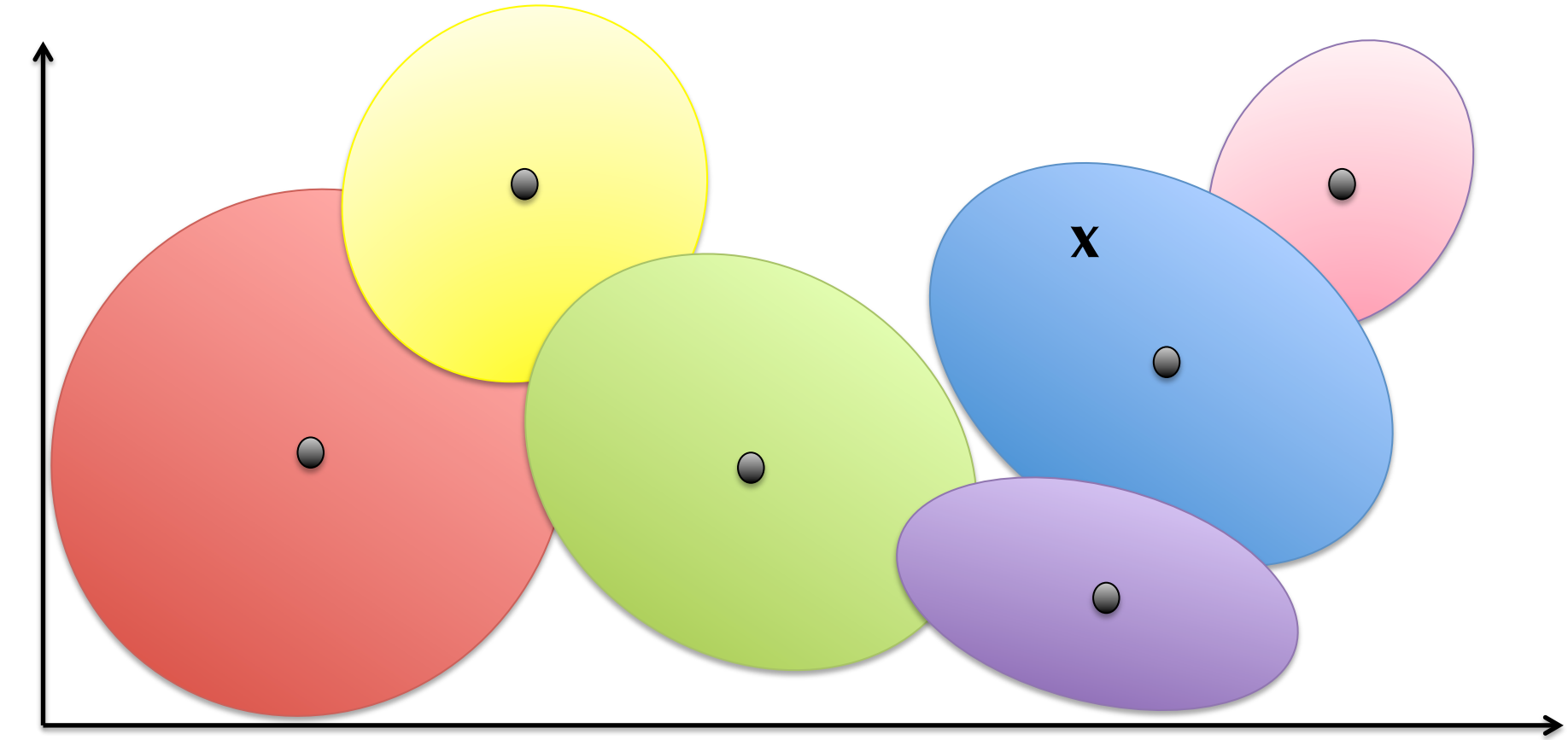
Models



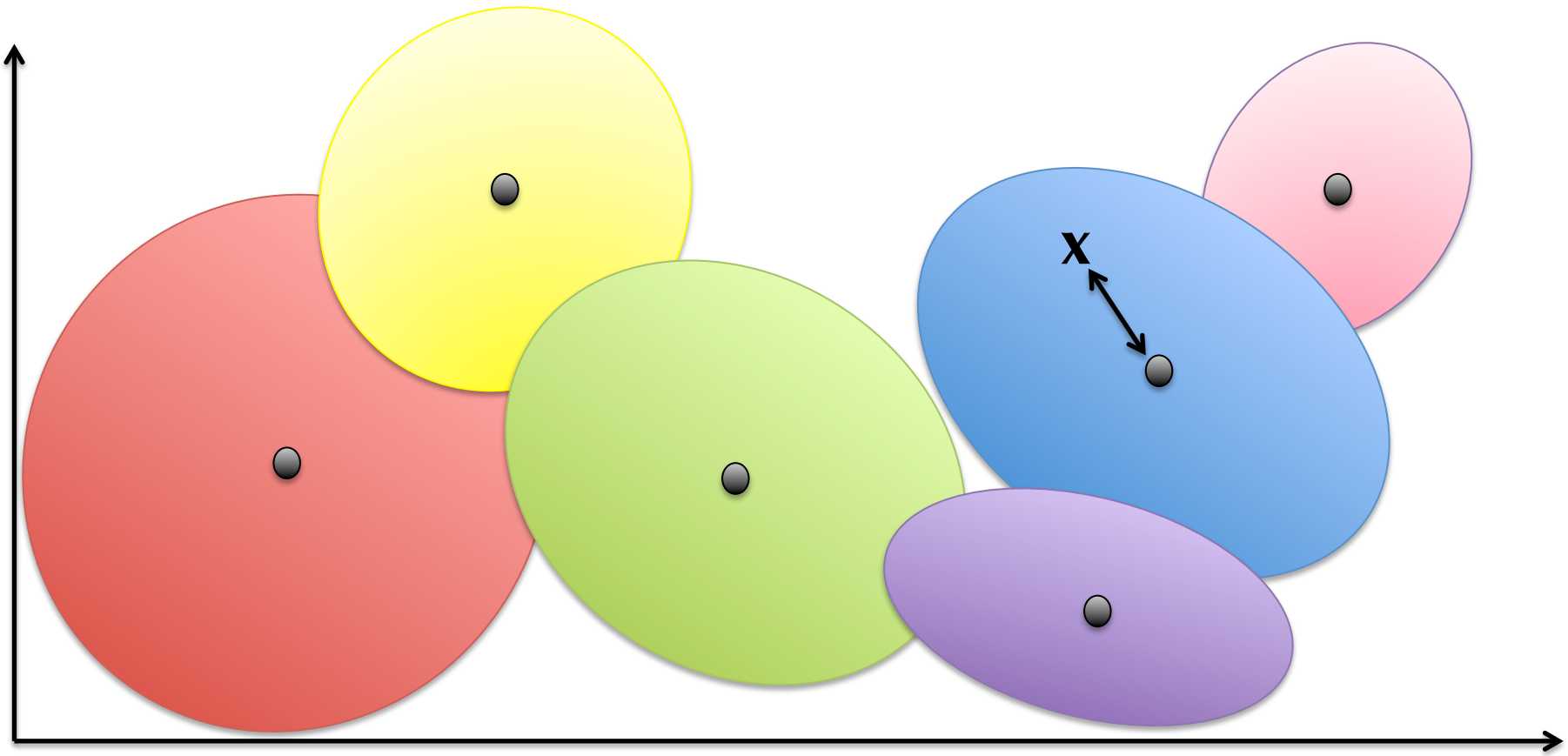
$$R(x,t) = \log \frac{p(x \mid t)}{\sum_{t' \neq t} p(x \mid t')\, p(t')}$$



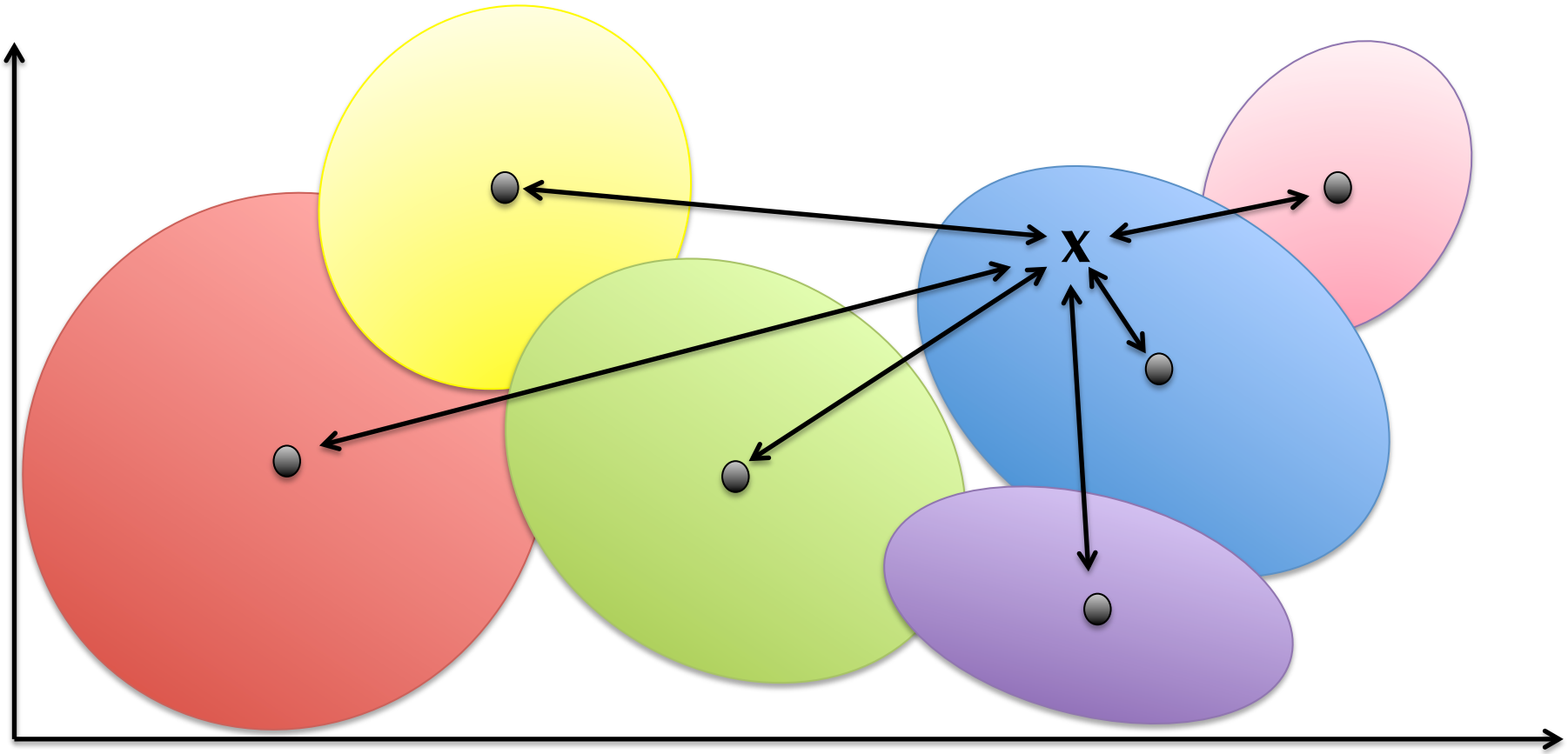
$$\boxed{R(x,t)} = \log \frac{p(x \mid t)}{\sum_{t' \neq t} p(x \mid t')\, p(t')}$$



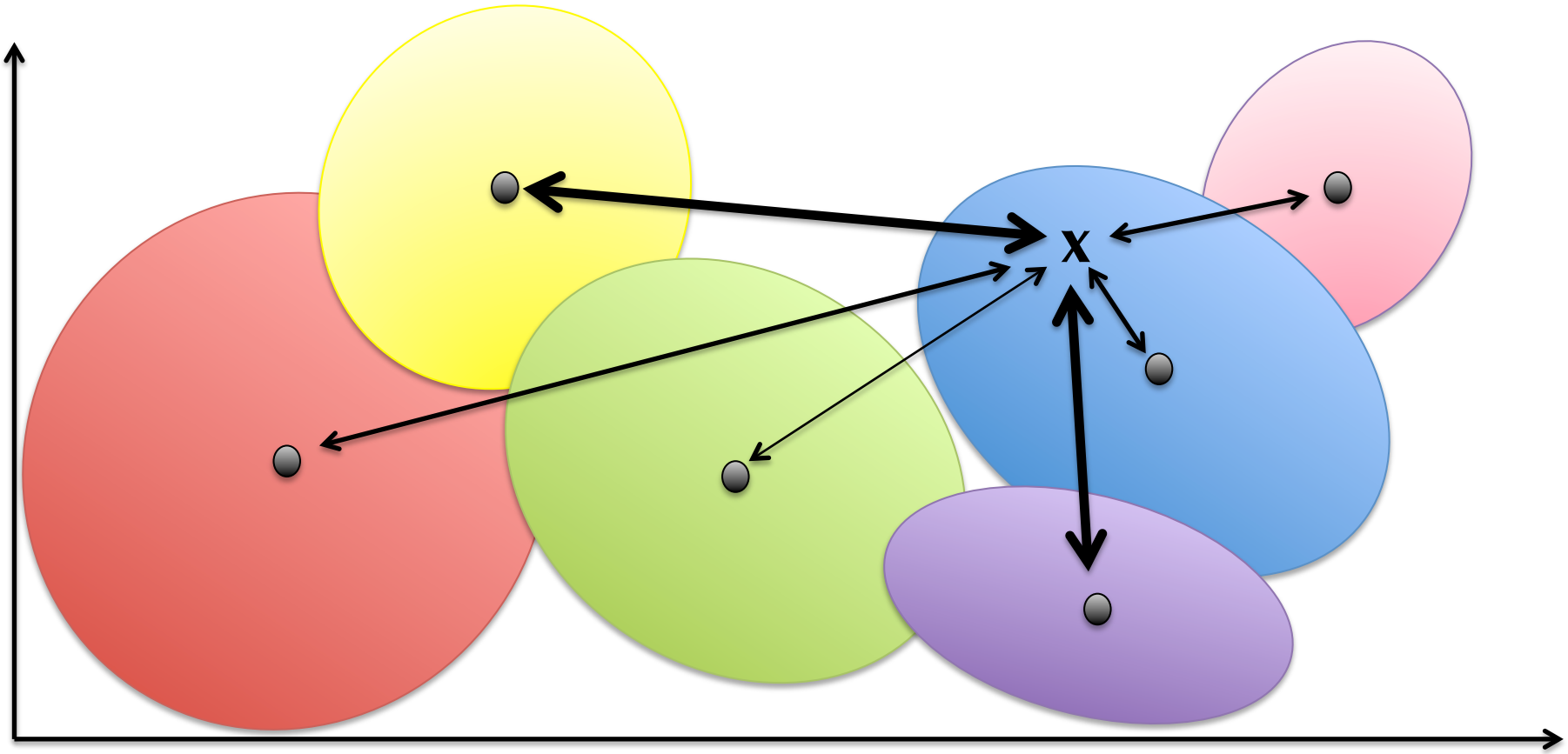
$$R(x,t) = \log \frac{\boxed{p(x \mid t)}}{\sum_{t' \neq t} p(x \mid t')\, p(t')}$$



$$R(x,t) = \log \frac{p(x \mid t)}{\sum_{t' \neq t} \boxed{p(x \mid t')} p(t')}$$



$$R(x,t) = \log \frac{p(x \mid t)}{\sum_{t' \neq t} p(x \mid t') \boxed{p(t')}}$$



- **Bayesian:** $$R(x,t) = \frac{p(x \mid t)}{\sum_{t' \neq t} p(x \mid t')p(t')}$$

- **Bayesian:** $$R(x,t) = \frac{p(x \mid t)}{\sum_{t' \neq t} p(x \mid t')p(t')}$$

- **Likelihood:** $$L(x,t) = p(x \mid t)$$

- **Bayesian:** $$R(x,t) = \frac{p(x \mid t)}{\sum_{t' \neq t} p(x \mid t')p(t')}$$
- **Likelihood:** $$L(x,t) = p(x \mid t)$$
- **Prototype:** $$P(x,t) = \exp\{-dist(x,\mu_t)\}$$
- **Exemplar:** $$E(x,t) = \sum_{x_j \in X_t} \exp\{-\lambda dist(x,x_j)\}$$

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	18	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
A	0																																								
B	0	2	2	2	2	2	2	2	2	4	6	6	6	6	4	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
C	0	6	6	6	6	6	6	8	14	16	14	12	12	12	10	10	8	8	6	6	6	6	4	4	4	4	4	4	4	6	6	4	4	4	4	6	6	6	6	6	6
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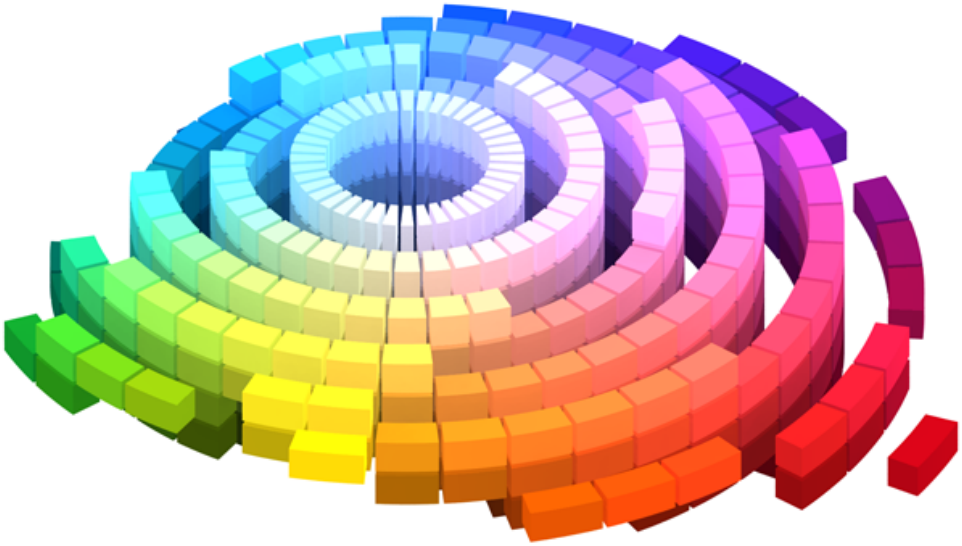

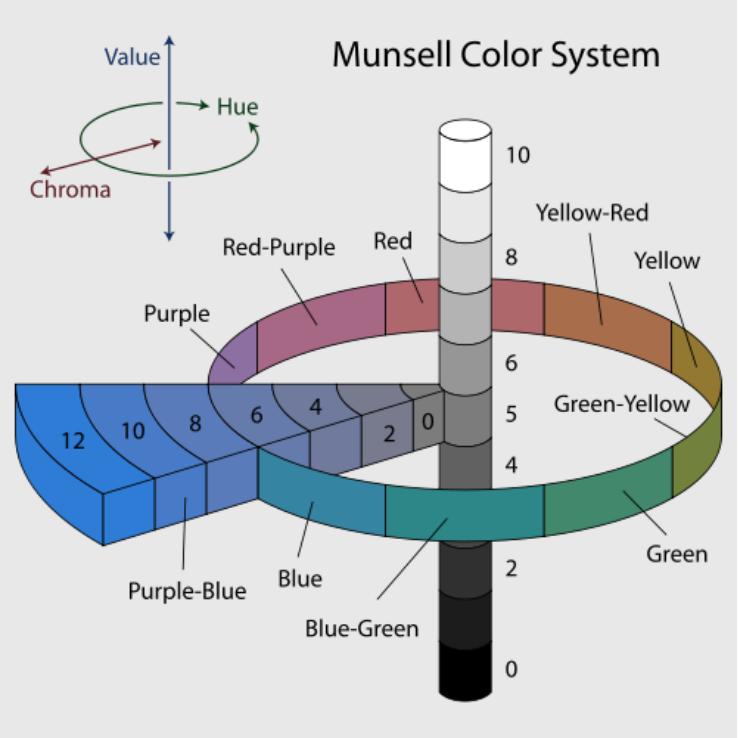

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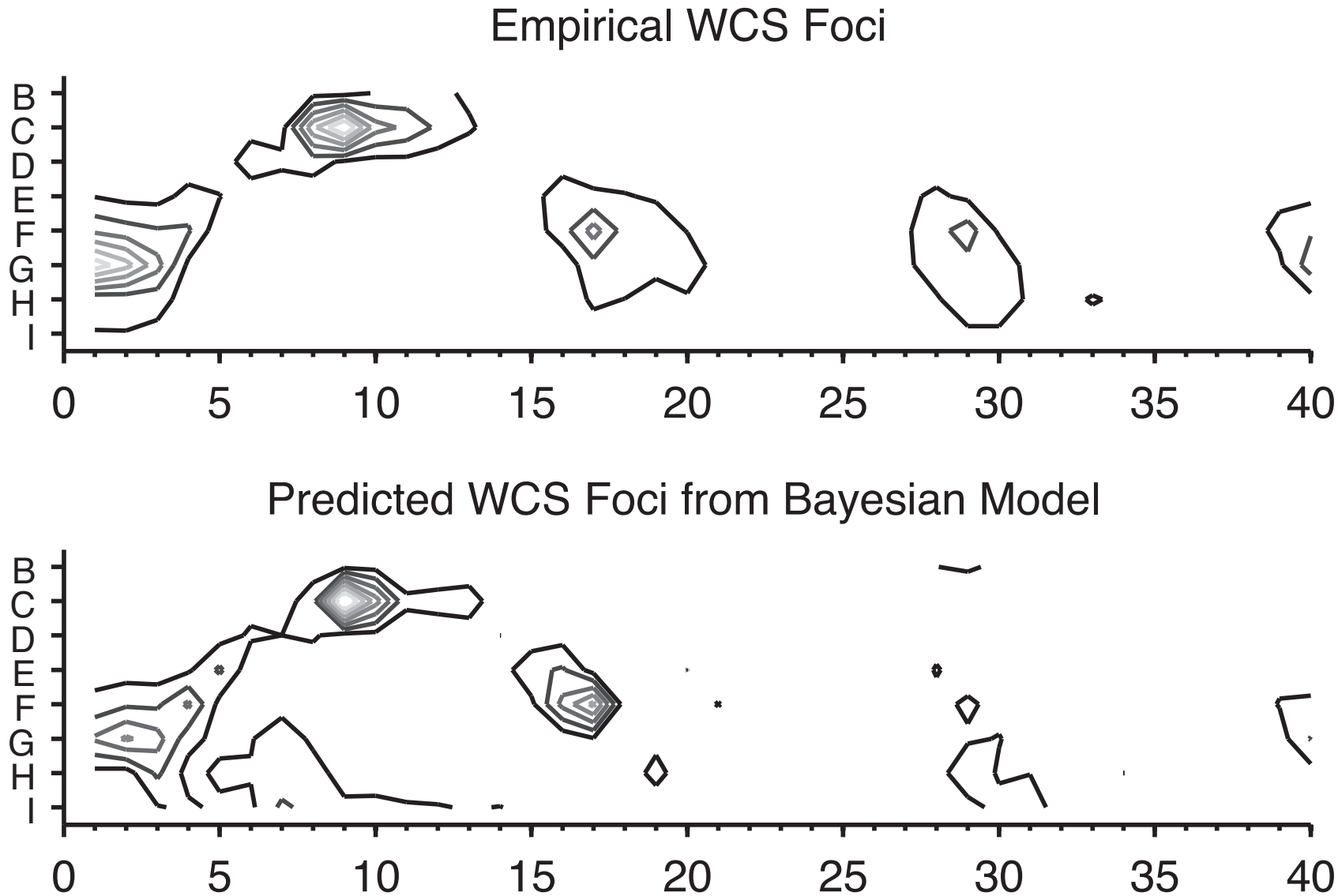
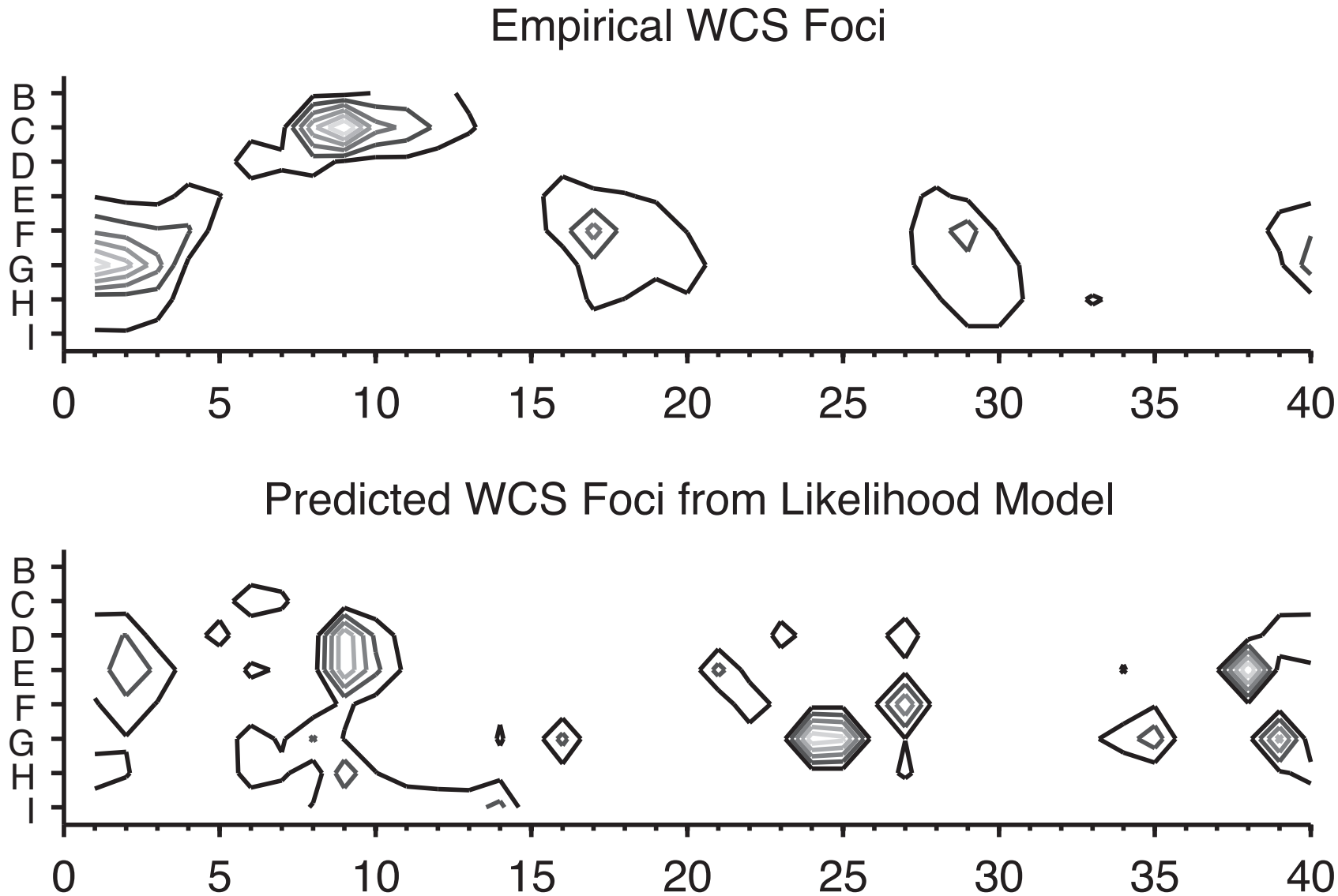
- **Chroma:** $$C(x,t) = \exp\{-dist(x,c_t)\}$$

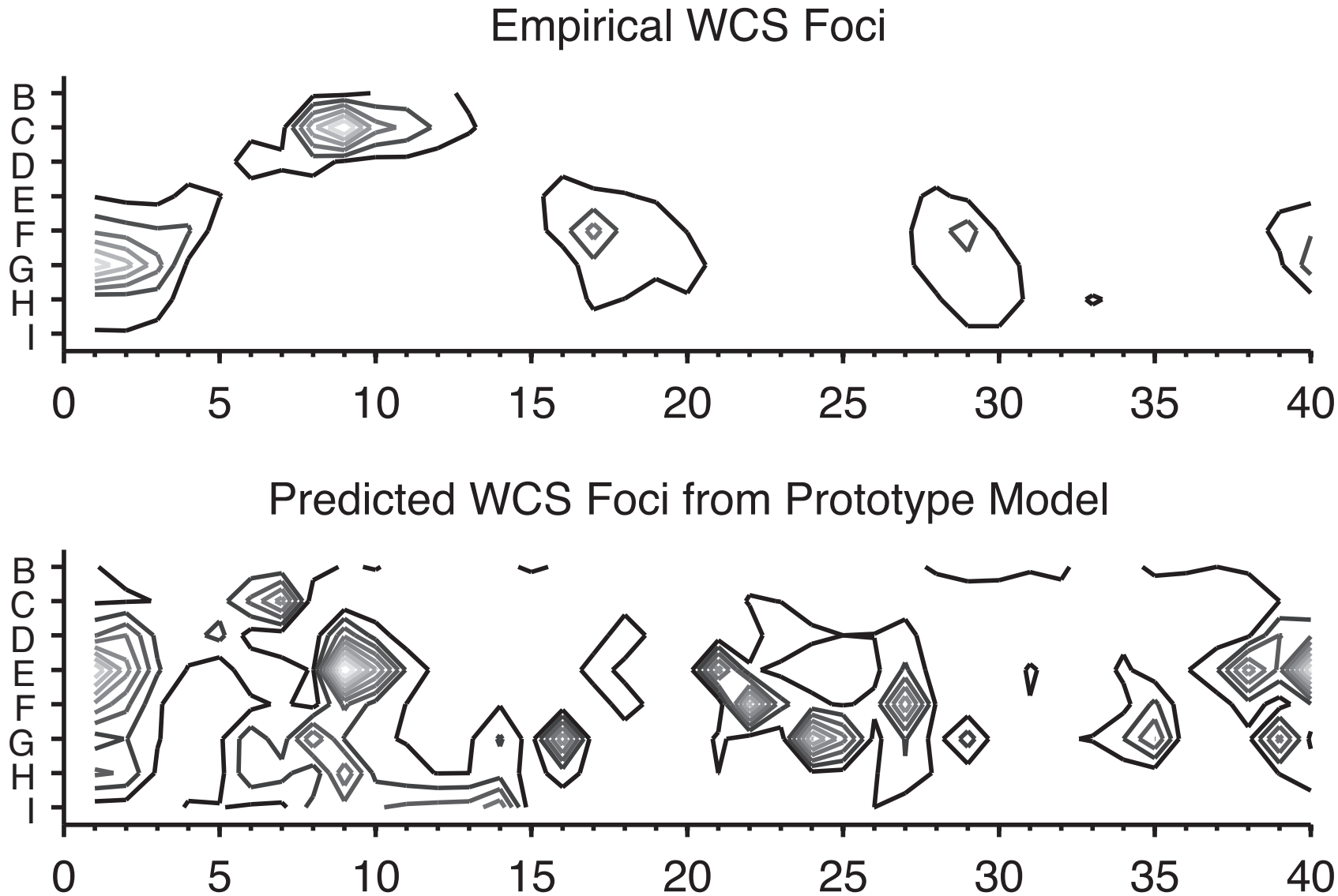
Distribution of foci / JSD



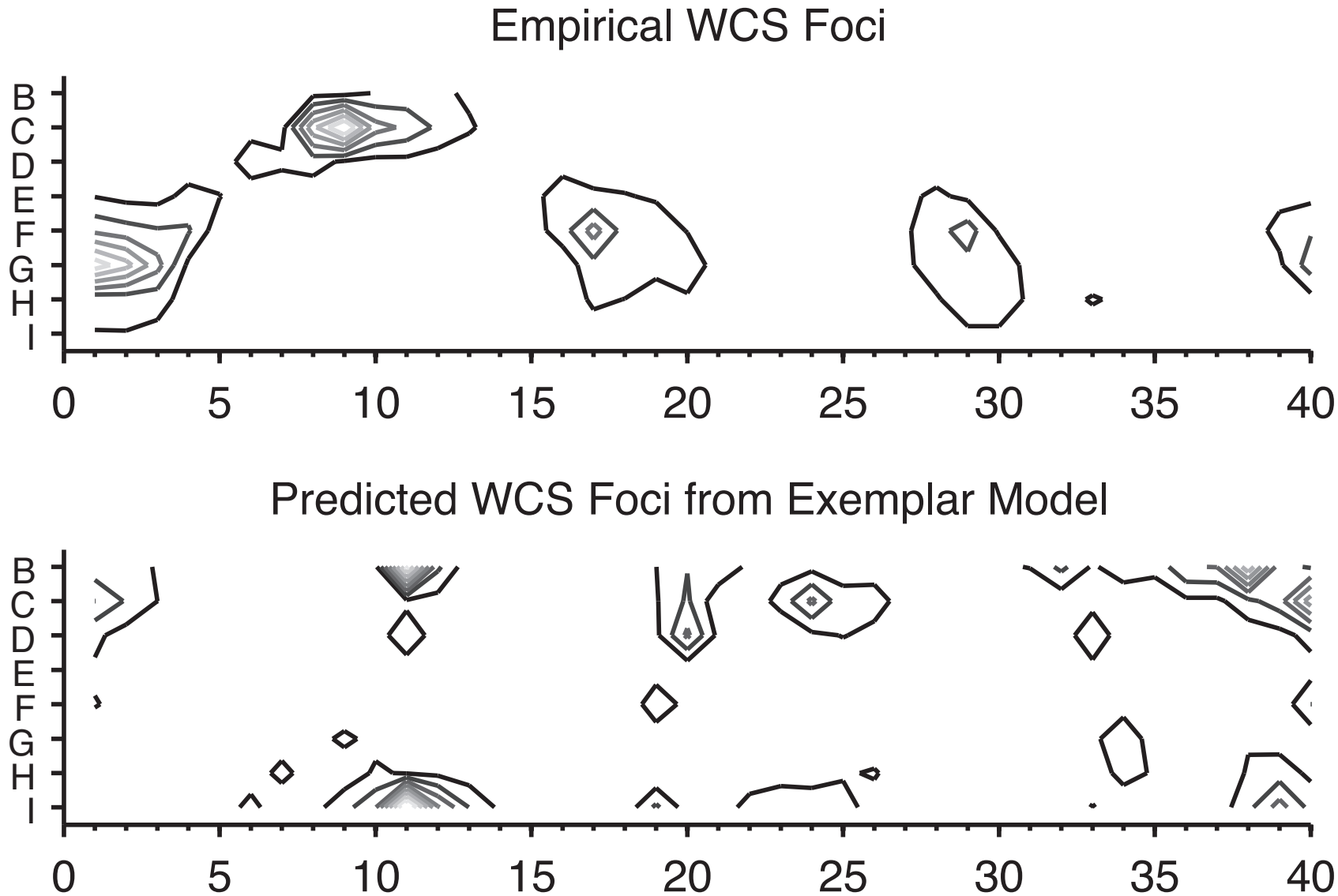
Jensen-Shannon Divergence: 0.0368



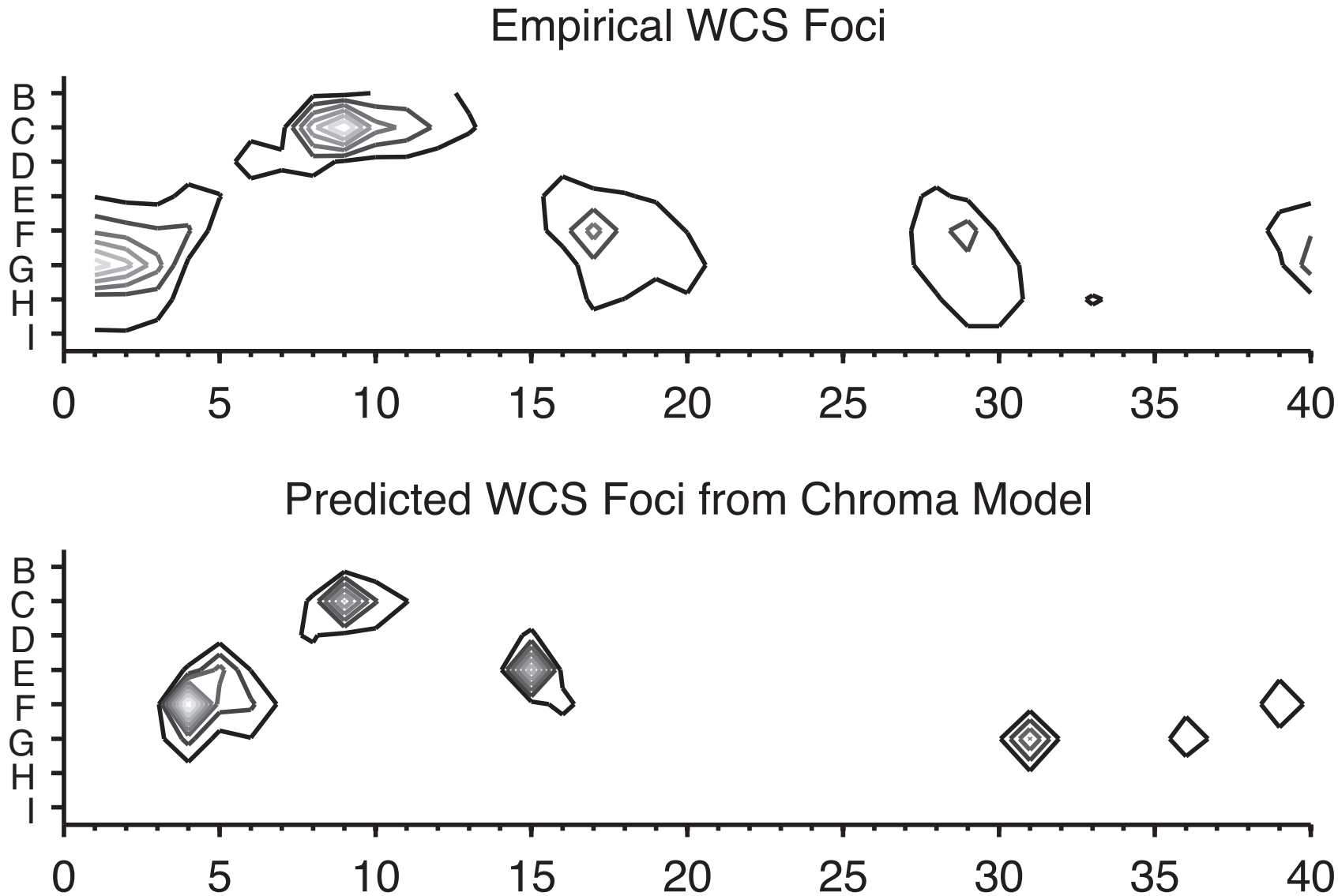
Jensen-Shannon Divergence: 0.1977



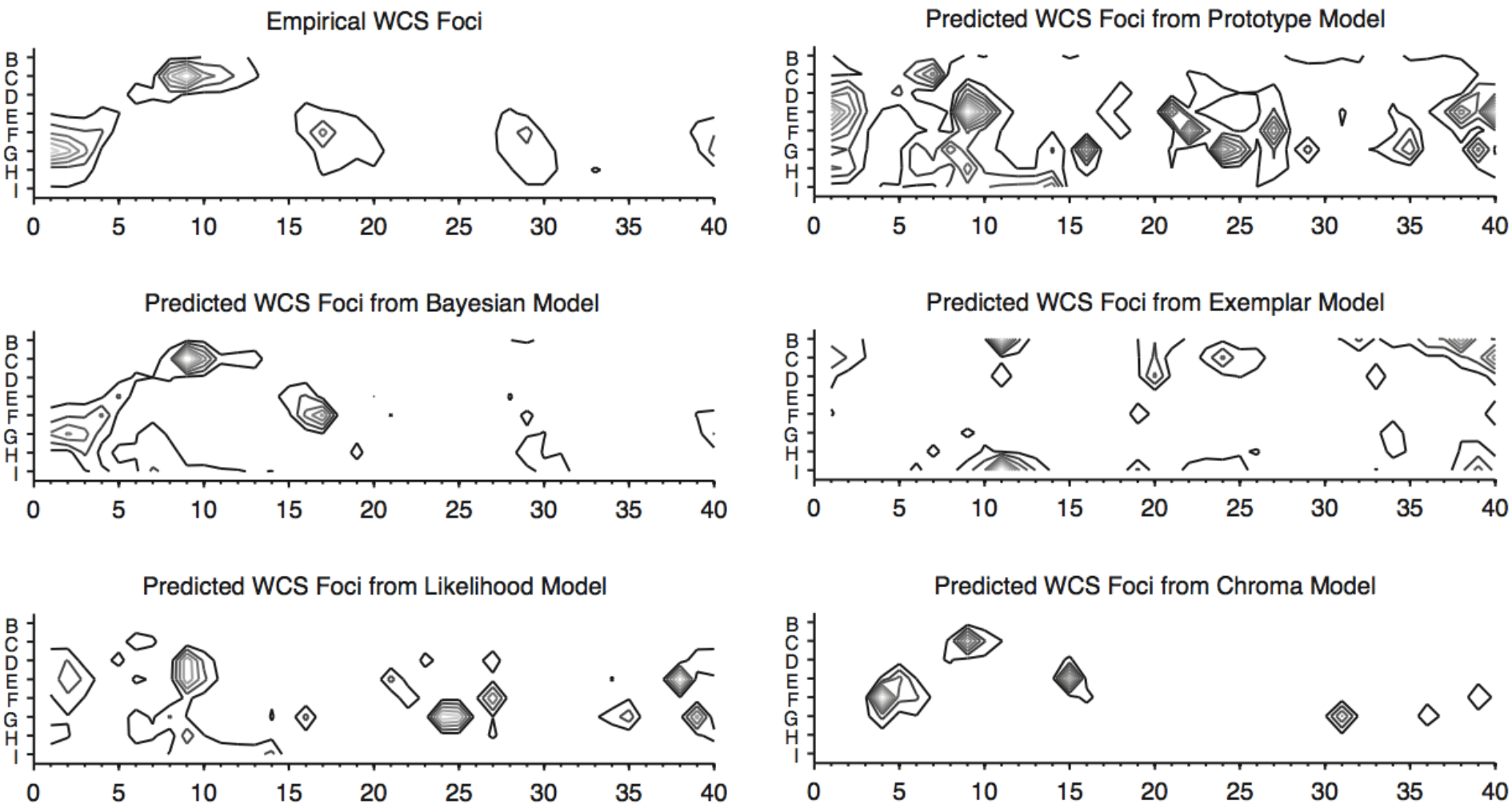
Jensen-Shannon Divergence: 0.1750



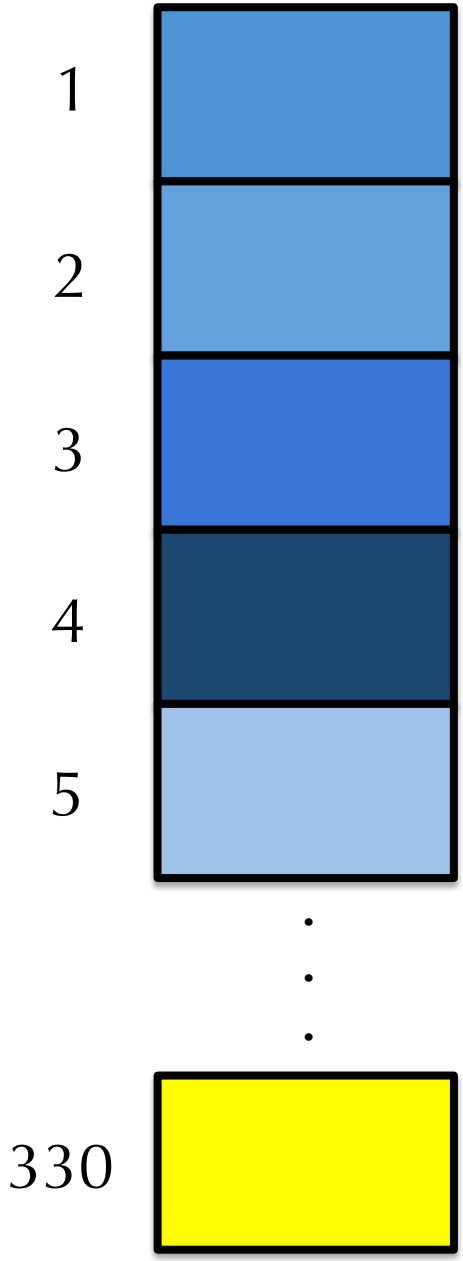
Jensen-Shannon Divergence: 0.1760



Jensen-Shannon Divergence: 0.1698


Empirical WCS Foci
Predicted WCS Foci from Prototype Model
Predicted WCS Foci from Bayesian Model
Predicted WCS Foci from Exemplar Model
Predicted WCS Foci from Likelihood Model
Predicted WCS Foci from Chroma Model
B C D E F G H I
0 5 10 15 20 25 30 35 40

Rank position metric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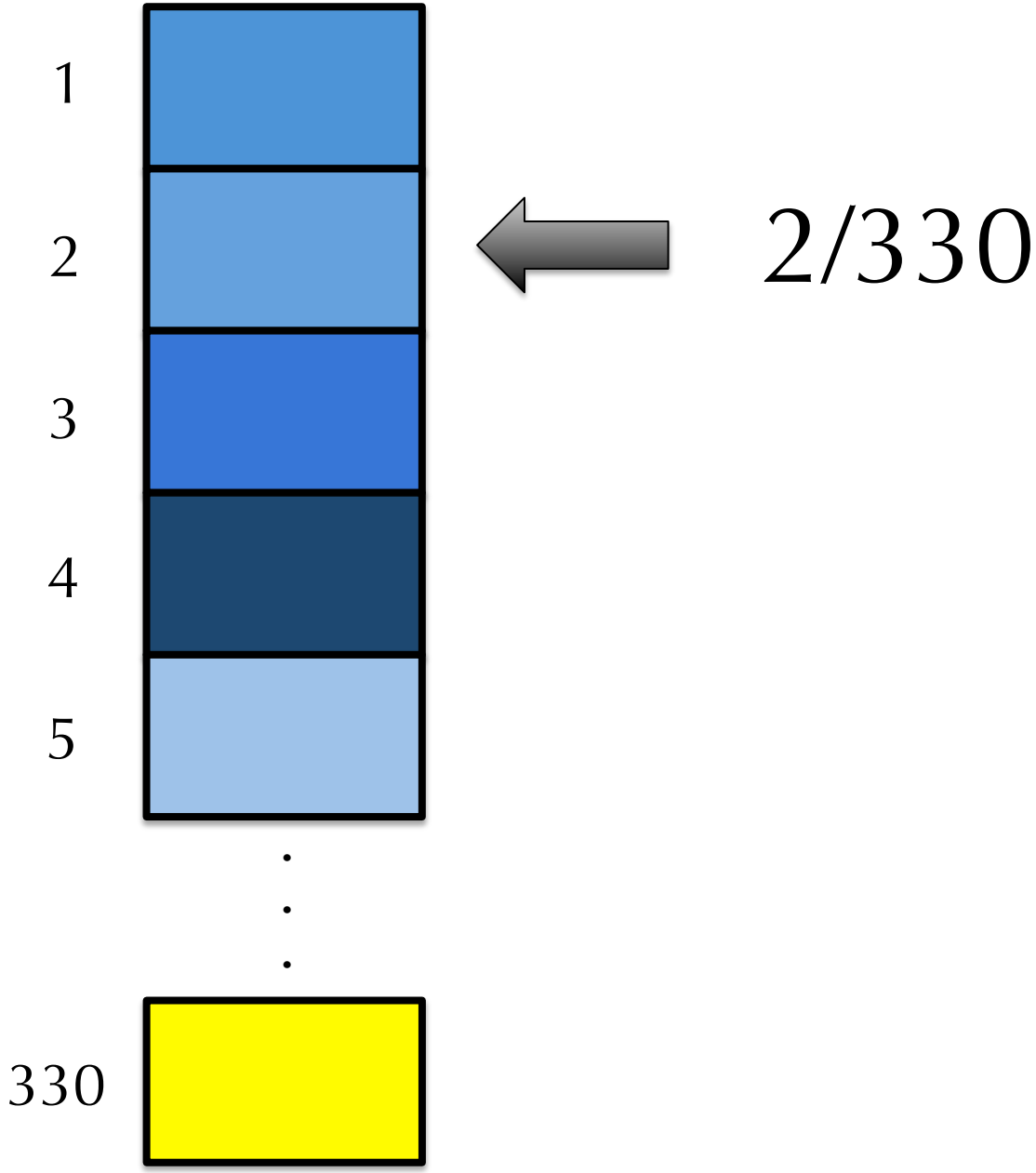
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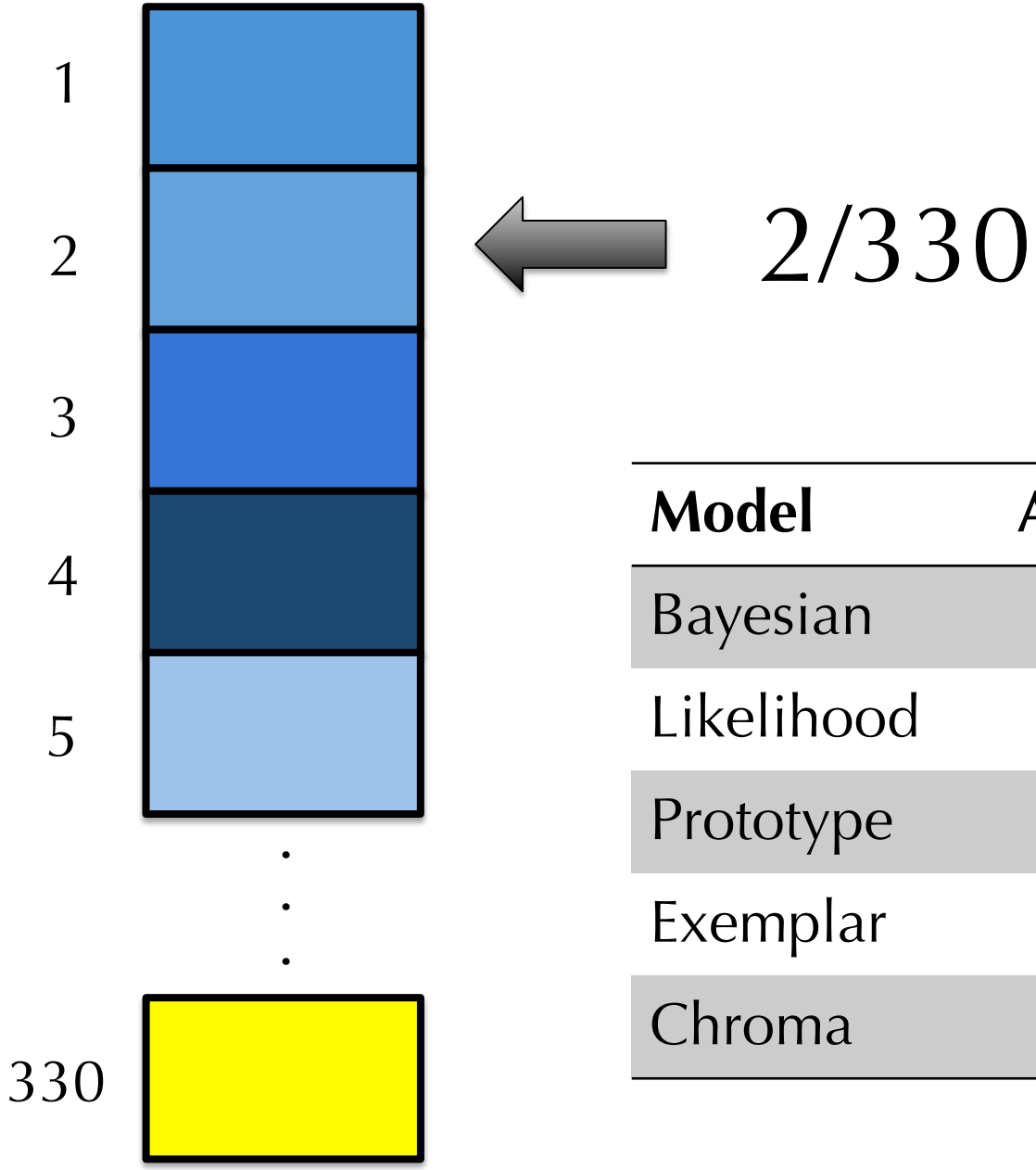
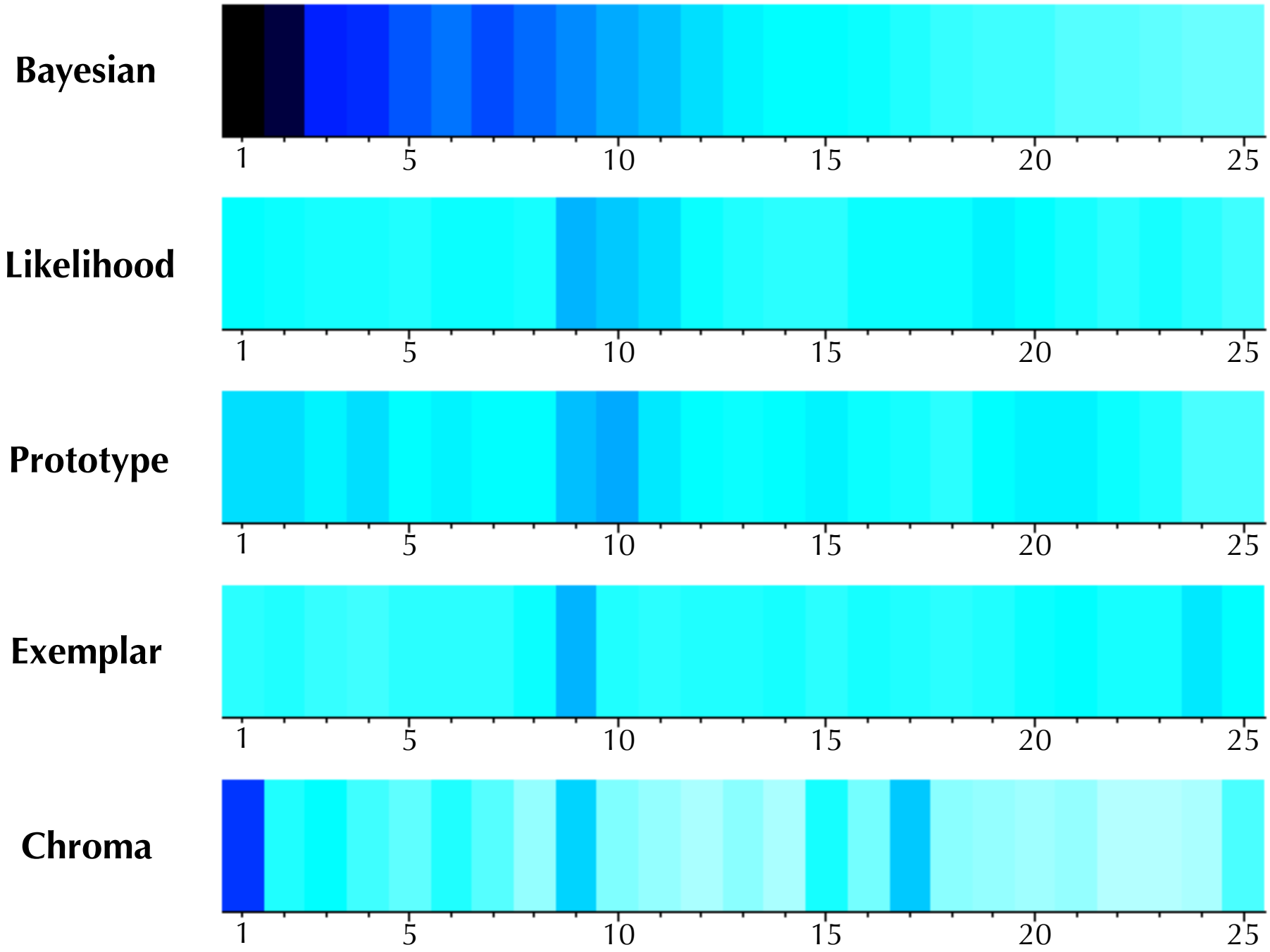


Model	Average Rank Position
Bayesian	0.1026
Likelihood	0.1381
Prototype	0.1559
Exemplar	0.1457
Chroma	0.2306


Bayesian
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Likelihood
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Prototype
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Exemplar
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Chroma
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Near-Optimal Partitions

A categorical partition of color space is *well-formed* if it maximizes *perceptual contrast* between categories.

$$sim(x, y) = \exp(-c \times dist(x, y)^2)$$ Similarity

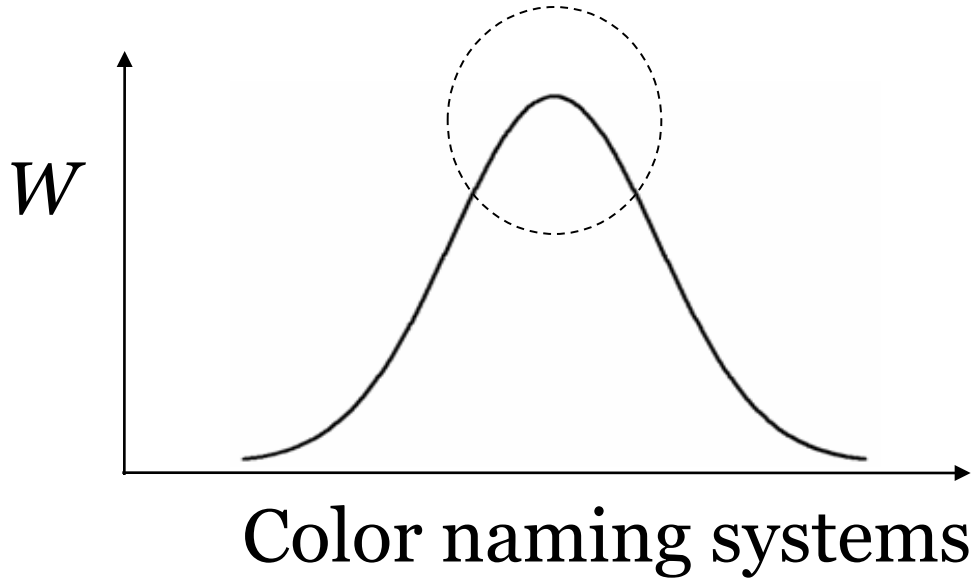
$$S_w = \sum_{\substack{(x,y): \\ cat(x)=cat(y)}} sim(x, y)$$ Within-category similarity

$$D_a = \sum_{\substack{(x,y): \\ cat(x)\neq cat(y)}} (1 - sim(x, y))$$ Cross-category contrast

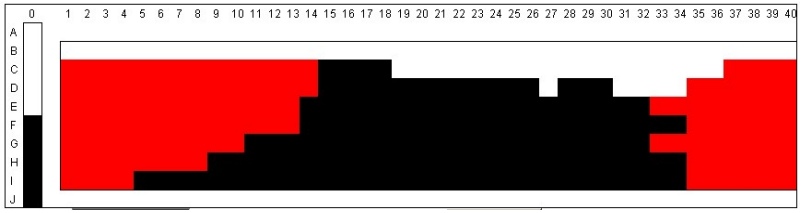
$$W = S_w + D_a$$ Well-formedness

General prediction

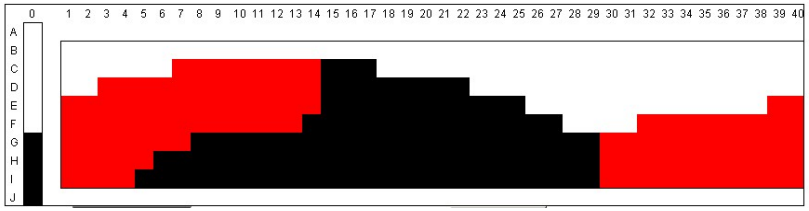
Natural color naming systems should be near-maximal in well-formedness.



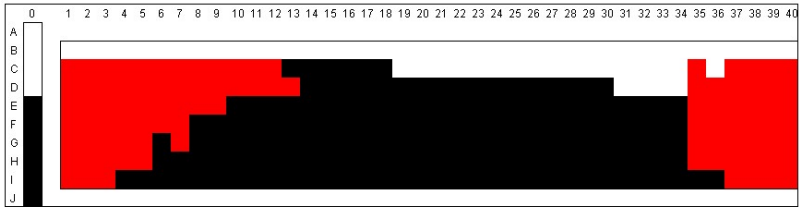
Wobé, Ivory Coast



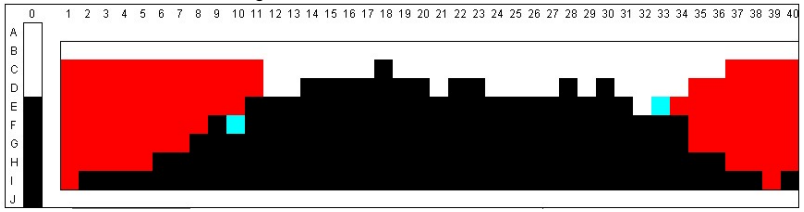
Model, n=3



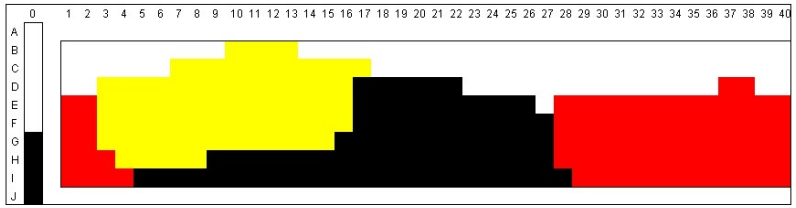
Ejagam, Nigeria/Cameroon



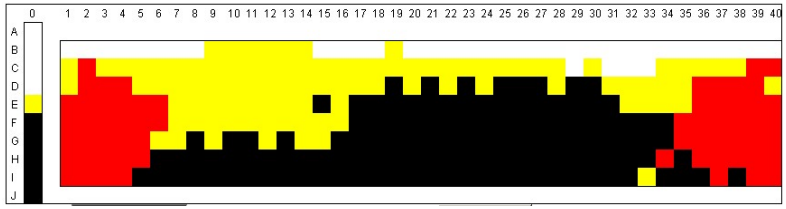
Bété, Ivory Coast



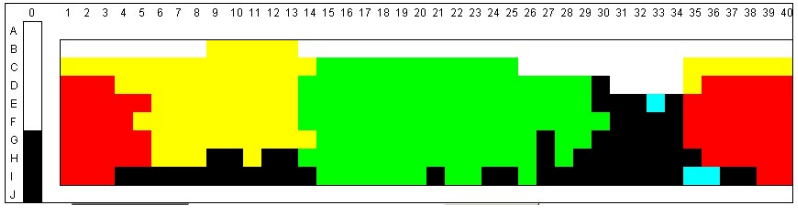
Model, n=4



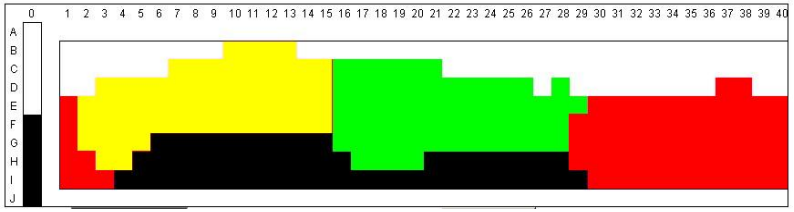
Culina, Peru/Brazil



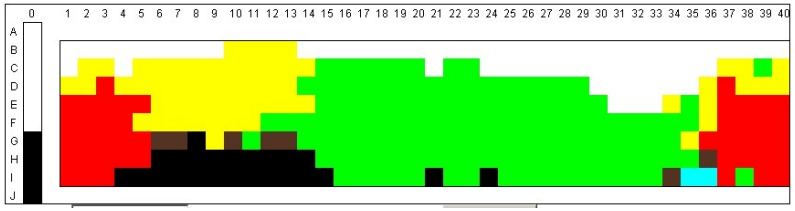
Iduna, Papua New Guinea



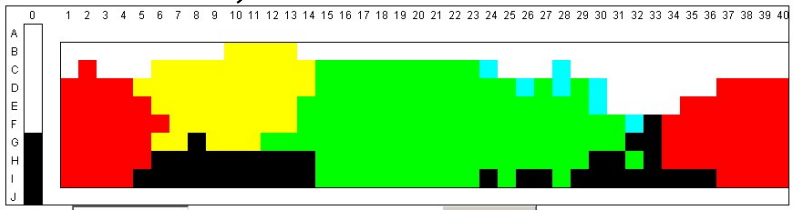
Model, n=5



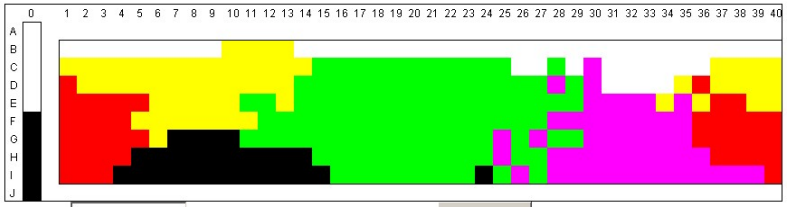
Cayapa, Ecuador



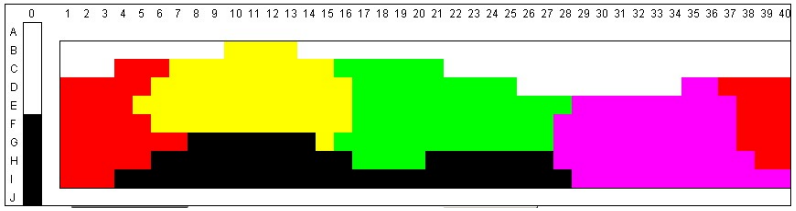
Colorado, Ecuador



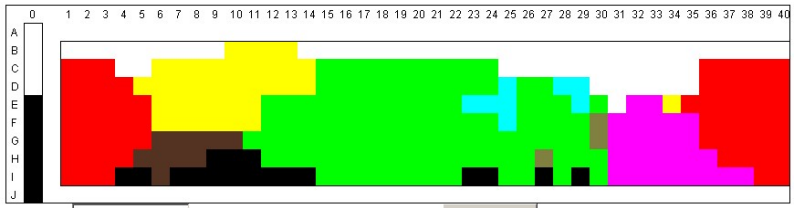
Buglere, Panama



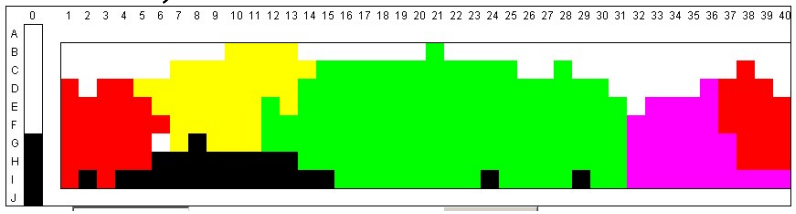
Model, n=6



Aguacatec, Guatemala



Cofán, Ecuador

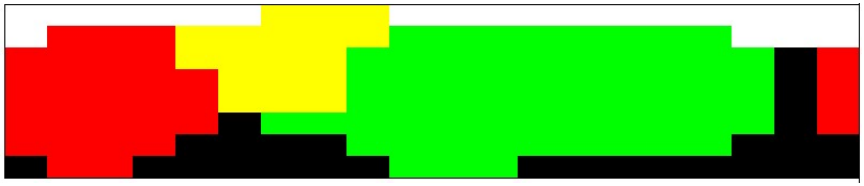


Prediction: Natural boundaries yield highest well-formedness.

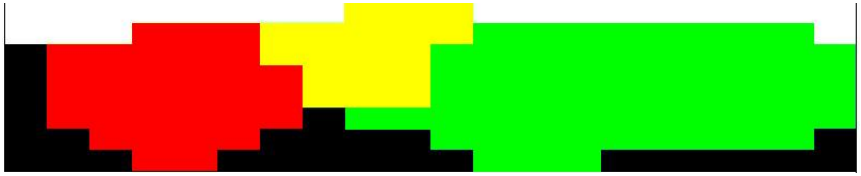
Berinmo

(Roberson et al, 2000)

rotated 4 columns

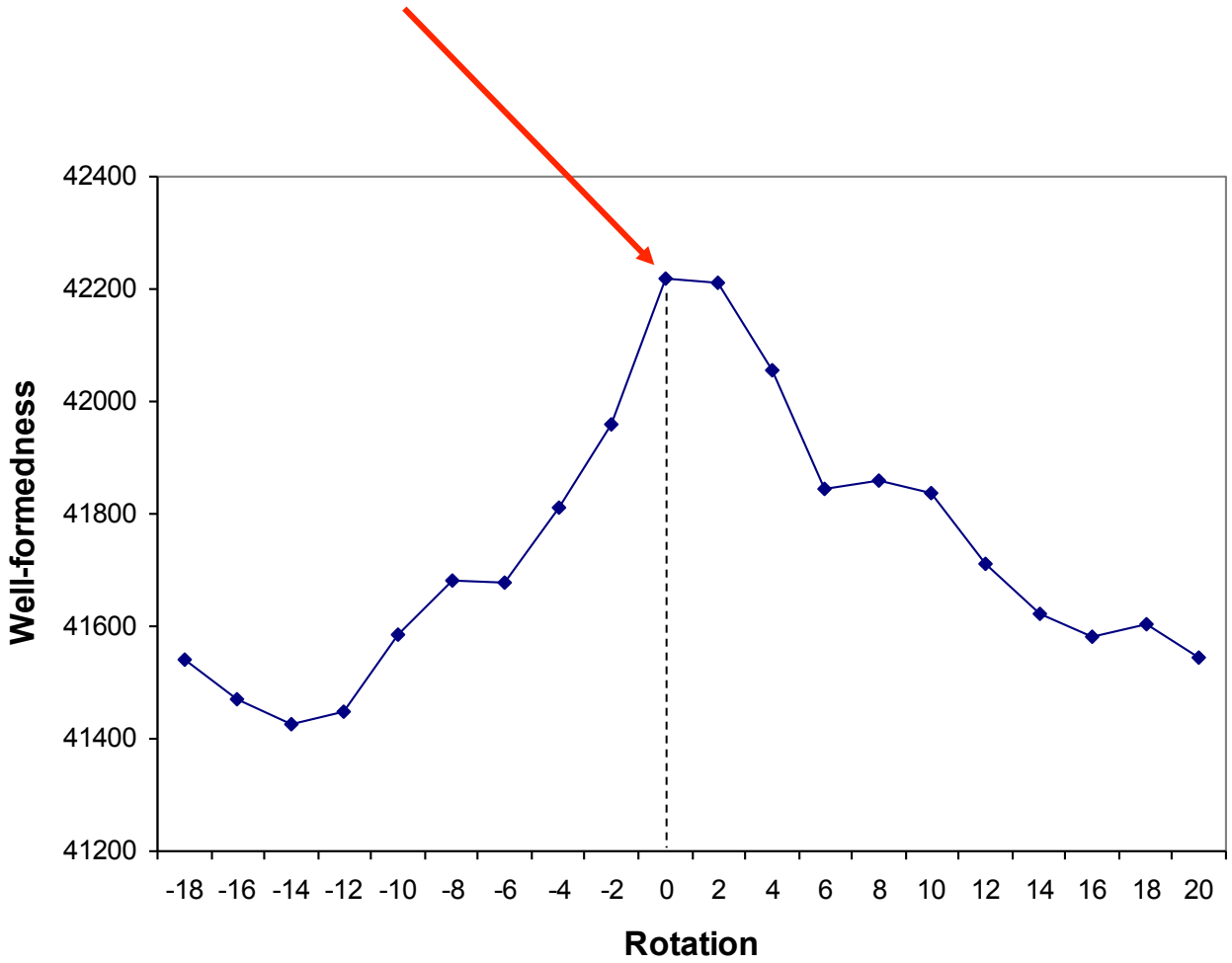


rotated 8 columns

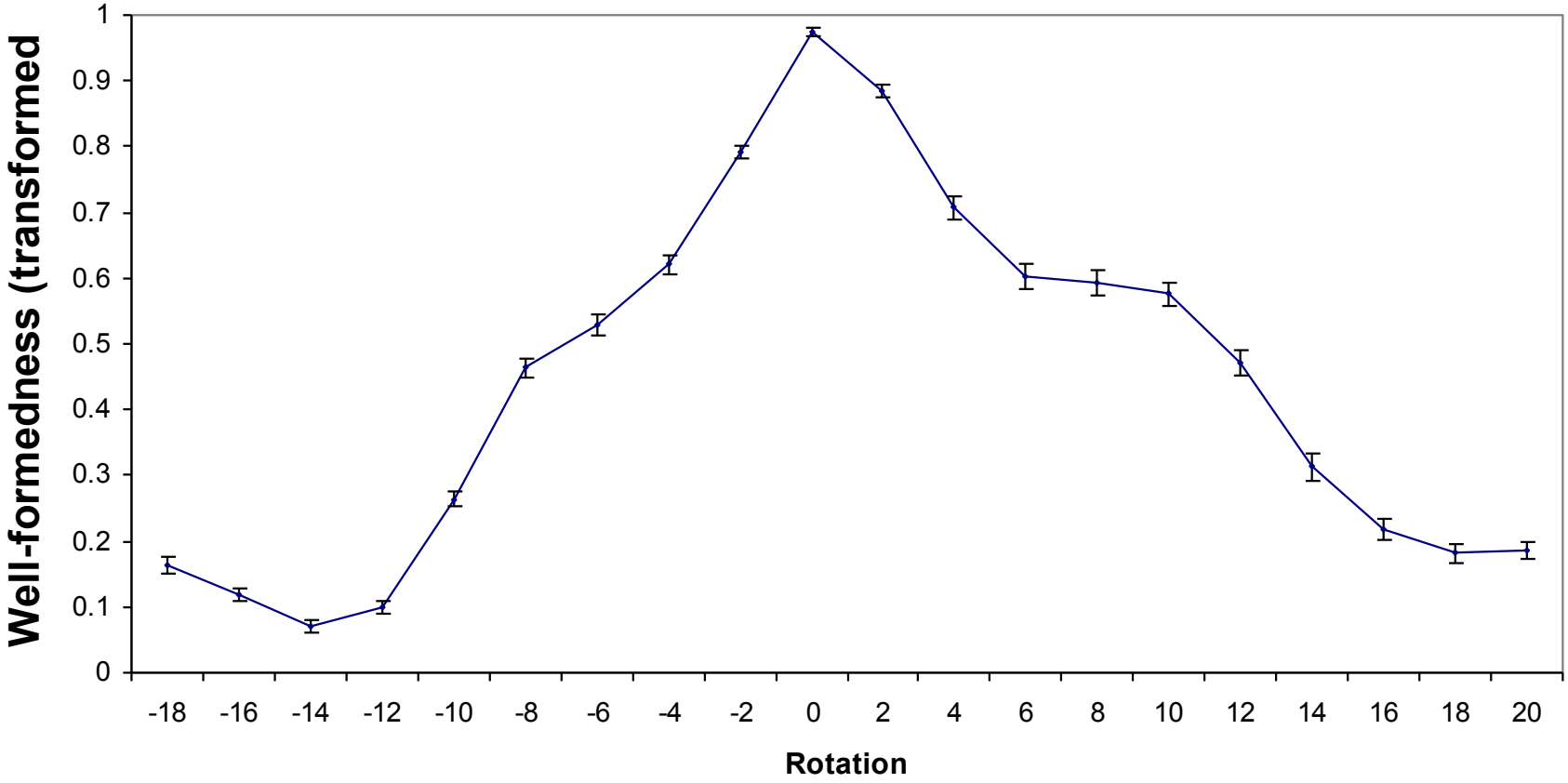


…

Confirmed.


42400
42200
42000
41800
41600
41400
41200
Well-formedness
-18 -16 -14 -12 -10 -8 -6 -4 -2 0 2 4 6 8 10 12 14 16 18 20
Rotation

All 110 WCS languages, averaged



Regier, T., Kay, P., & Khetarpal, N. (2007). *PNAS*.

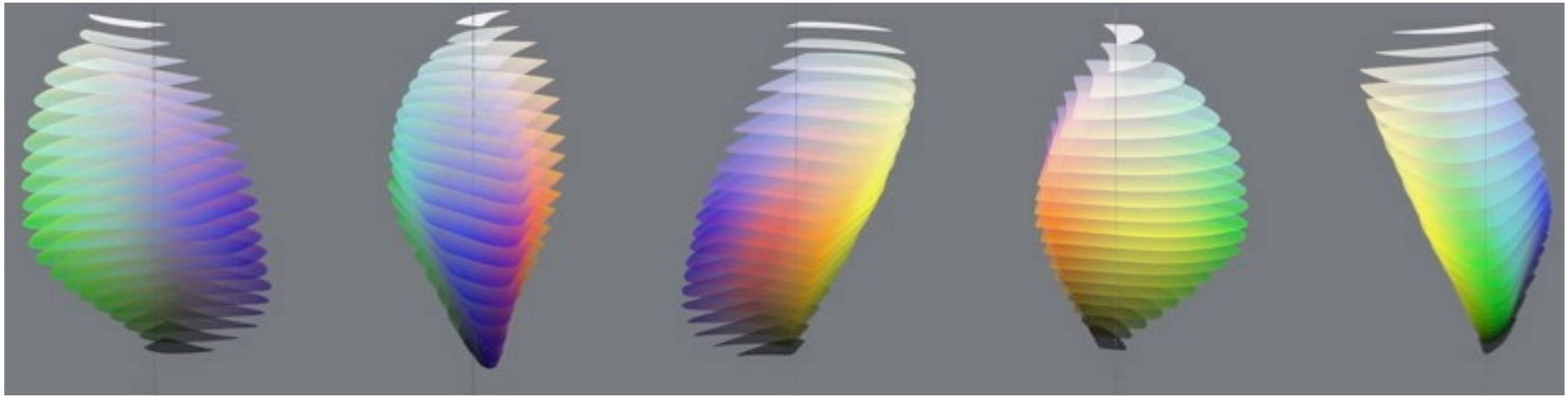
Recap so far

universalist: universal set of foci determine language category boundaries

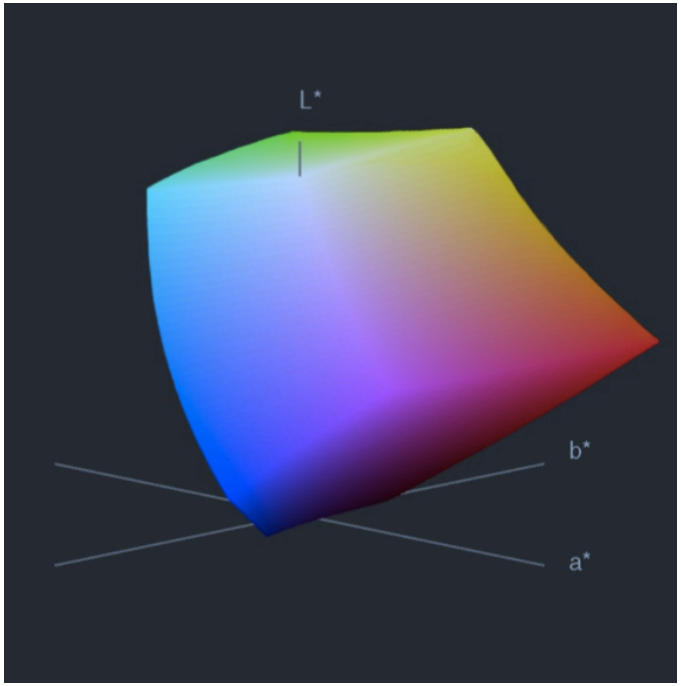
relativist: color categories defined at their boundaries, foci are after-effect

perceptual: color naming in terms of the overall shape of perceptual color space

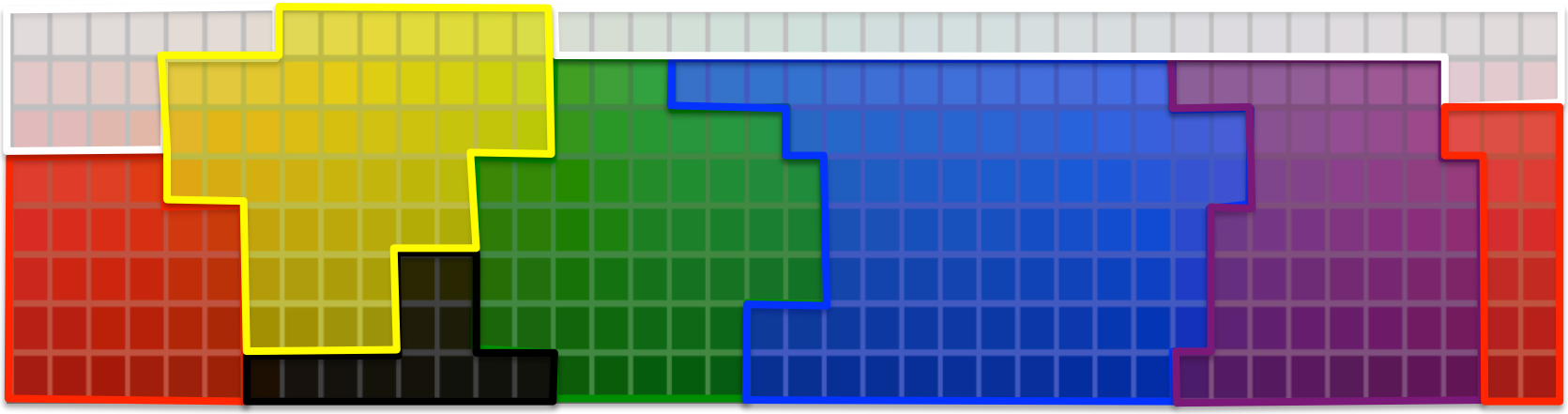
our proposal: foci are “representative” examples of color categories from boundaries



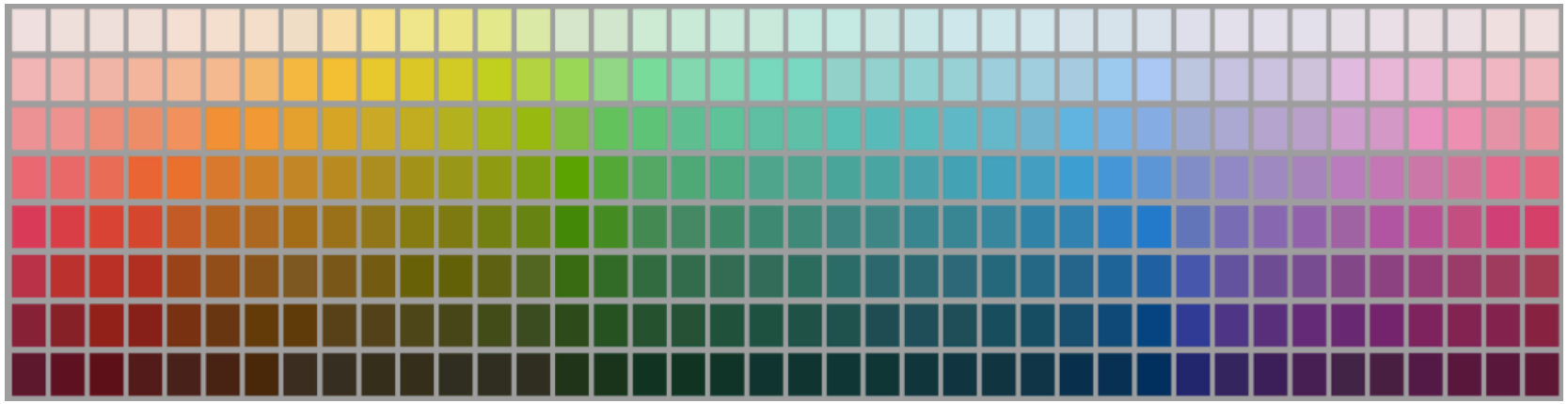
"one possible explanation for universals in color naming is.. the irregular shape of the color space.. hue interacts with saturation and lightness to produce several large bumps, one large bump is focal yellow, and another at focal red.. we assume that the names that get assigned to color space.. are likely to be those names which are most informative about color"



(Jameson and D'Andrade, 1997)

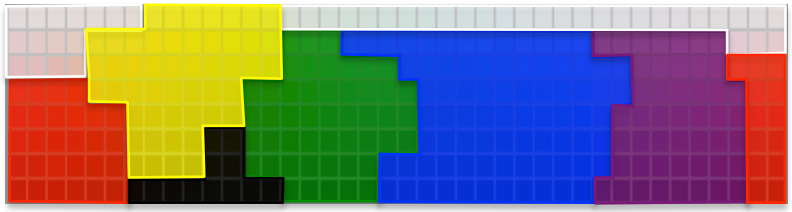


GROUPED



How do we discriminate?

Answer: Languages with unusual boundaries

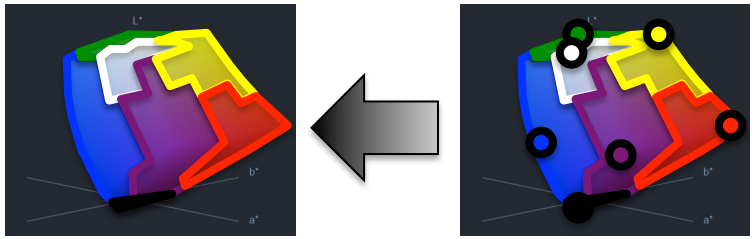


How do we discriminate?

Answer: Languages with unusual boundaries

Predictions

Universal Foci:



Derived Foci: