Information-Theoretic Probing with Minimum Description Length

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TLDR

$$\mathcal{L}_{\text{Minimum Description Length}} = \mathcal{L}_{\text{Model}} + \mathcal{L}_{\text{Data}}$$

TLDR

Choose the model that gives the shortest description.

$$\mathcal{L}_{\text{Minimum Description Length}} = \mathcal{L}_{\text{Model}} + \mathcal{L}_{\text{Data}}$$

Rissanen, Jorma. "Modeling by shortest data description." *Automatica* 14.5 (1978): 465-471.

TLDR

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$$\mathcal{L}_{\text{Minimum Description Length}} = \mathcal{L}_{\text{Model}} + \mathcal{L}_{\text{Data}}$$

Variational Inference & Bayesian Learning

TLDR

$$\mathcal{L}_{\text{Minimum Description Length}} = \mathcal{L}_{\text{Model}} + \mathcal{L}_{\text{Data}}$$

$$\mathcal{L}_{\text{Var}} = \mathrm{KL}(\beta \parallel \alpha) - \mathbb{E}_{\theta \sim \beta} \sum_{i=1}^{n} \log_2 p_\theta(y_i | x_i)$$

TLDR

$$\mathcal{L}_{\text{Minimum Description Length}} = \mathcal{L}_{\text{Model}} + \mathcal{L}_{\text{Data}}$$

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$$\mathcal{L}_{\text{Online}} = t_1 \log_2 K - \sum_{i=1}^{S-1} \log_2 p_{\theta_i}(y_{t_i+1:t_{i+1}} | x_{t_i+1:t_{i+1}})$$

TLDR

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Resources

mdl paper

mdl code

mdl blog

bayesian layers paper

bits-back argument paper

probabilistic graphical models course

Models are doing pretty well

GLUE

NLI	MNLI, QNLI, RTE, Winograd NLI
Other Semantic Tasks	Semantic Textual Similarity, Stanford Sentiment Treebank, MR Paraphrase
Acceptability	Cola

GLUE

T5	90.3
Human Baseline	87.1
BERT++	80.5
BERT	78.1

SuperGLUE

Multi-Sentence Understanding

Common Sense

Non-trivial QA

SuperGLUE

Human Baseline	89.8
T5	89.3
BERT++	71.5
BERT	69.0

Why do the models
behave the way they do?

What do models learn?

Diagnostic classifiers; “probes”.

Diagnostic classifiers; “probes”.

Ian Tenney, Patrick Xia, Berlin Chen, Alex Wang, Adam Poliak, R Thomas McCoy, Najoung Kim, Benjamin Van Durme, Sam Bowman, Dipanjan Das, and Ellie Pavlick. 2019. What do you learn from context? probing for sentence structure in contextualized word representations. In International Conference on Learning Representations.

Tenney, Ian, Dipanjan Das, and Ellie Pavlick. "Bert rediscovers the classical nlp pipeline." arXiv preprint arXiv:1905.05950 (2019).

Zhang, Kelly W., and Samuel R. Bowman. "Language modeling teaches you more syntax than translation does: Lessons learned through auxiliary task analysis." arXiv preprint arXiv:1809.10040 (2018).

Kim, Najoung, et al. "Probing what different NLP tasks teach machines about function word comprehension." arXiv preprint arXiv:1904.11544 (2019).

Warstadt, Alex, et al. "Investigating BERT's Knowledge of Language: Five Analysis Methods with NPIs." arXiv preprint arXiv:1909.02597 (2019).

Clark, Kevin, et al. "What Does BERT Look At? An Analysis of BERT's Attention." arXiv preprint arXiv:1906.04341 (2019).

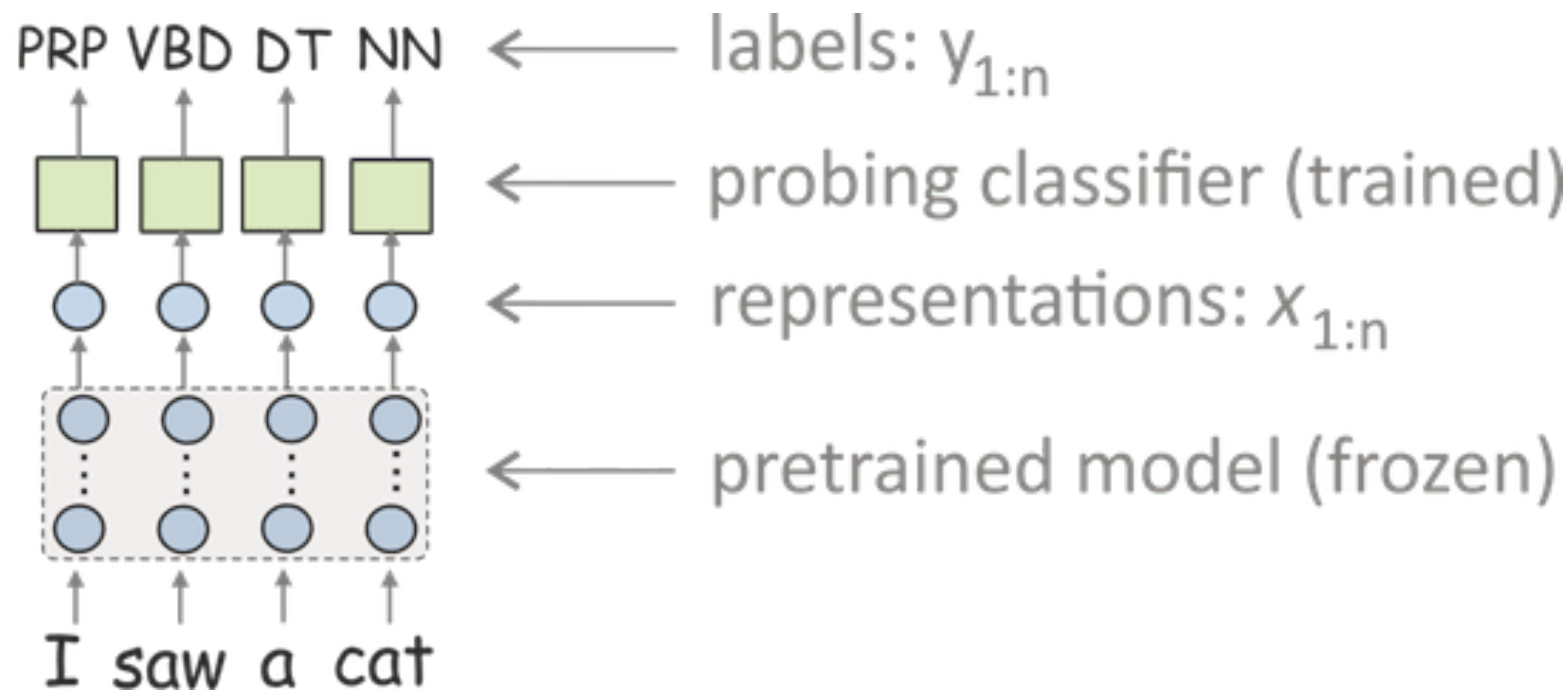
Goldberg, Yoav. "Assessing BERT's Syntactic Abilities." arXiv preprint arXiv:1901.05287 (2019).

Conneau, Alexis, et al. "What you can cram into a single vector: Probing sentence embeddings for linguistic properties." arXiv preprint arXiv:1805.01070 (2018).

…

Goal:
predict labels

Measure:
probe accuracy

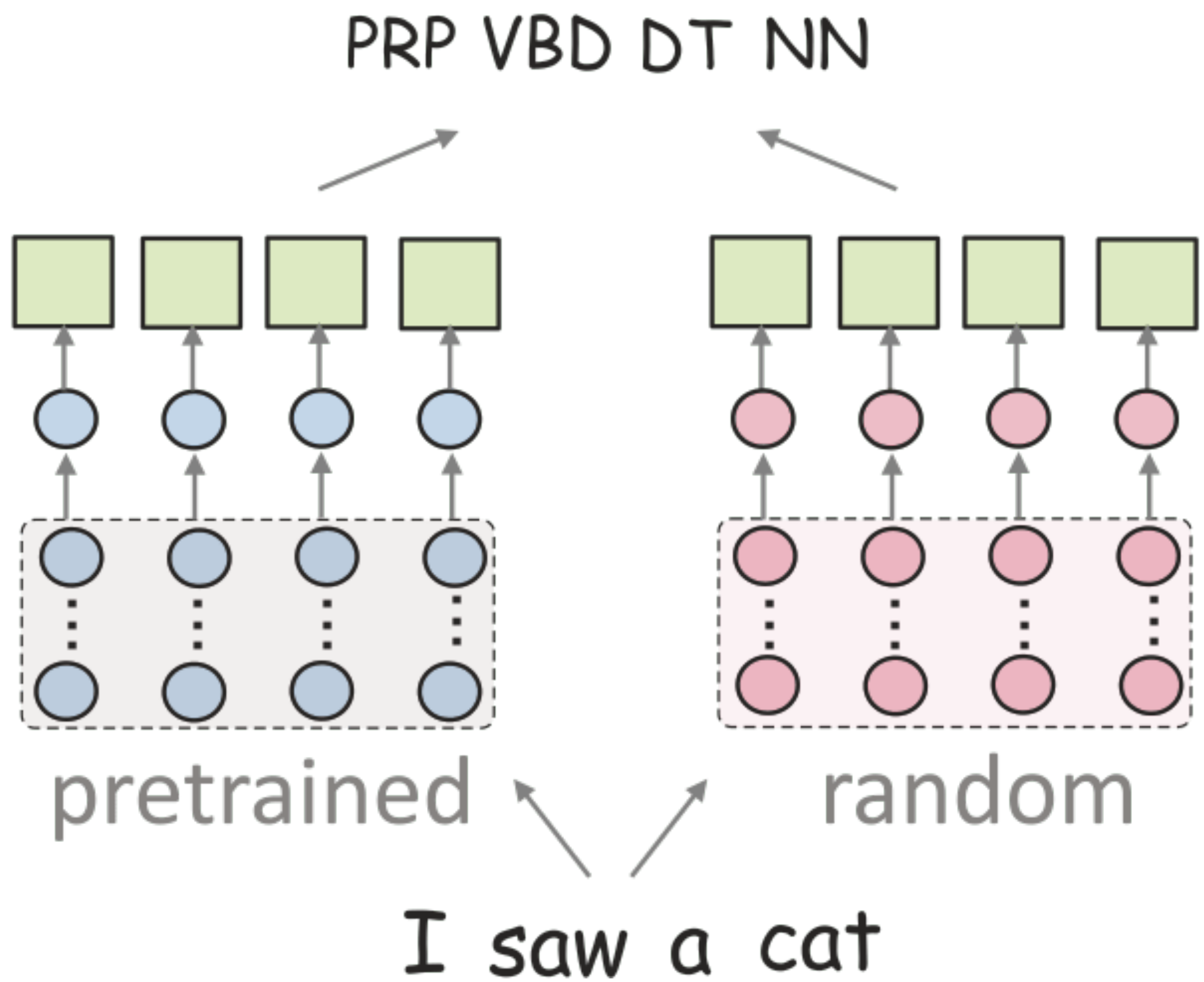


https://lena-voita.github.io/posts/mdl_probes.html

1. Models with random weights report similar accuracies to models with trained weights.

Zhang, Kelly W., and Samuel R. Bowman. "Language modeling teaches you more syntax than translation does: Lessons learned through auxiliary task analysis." *arXiv preprint arXiv:1809.10040* (2018).

Model: trained vs random



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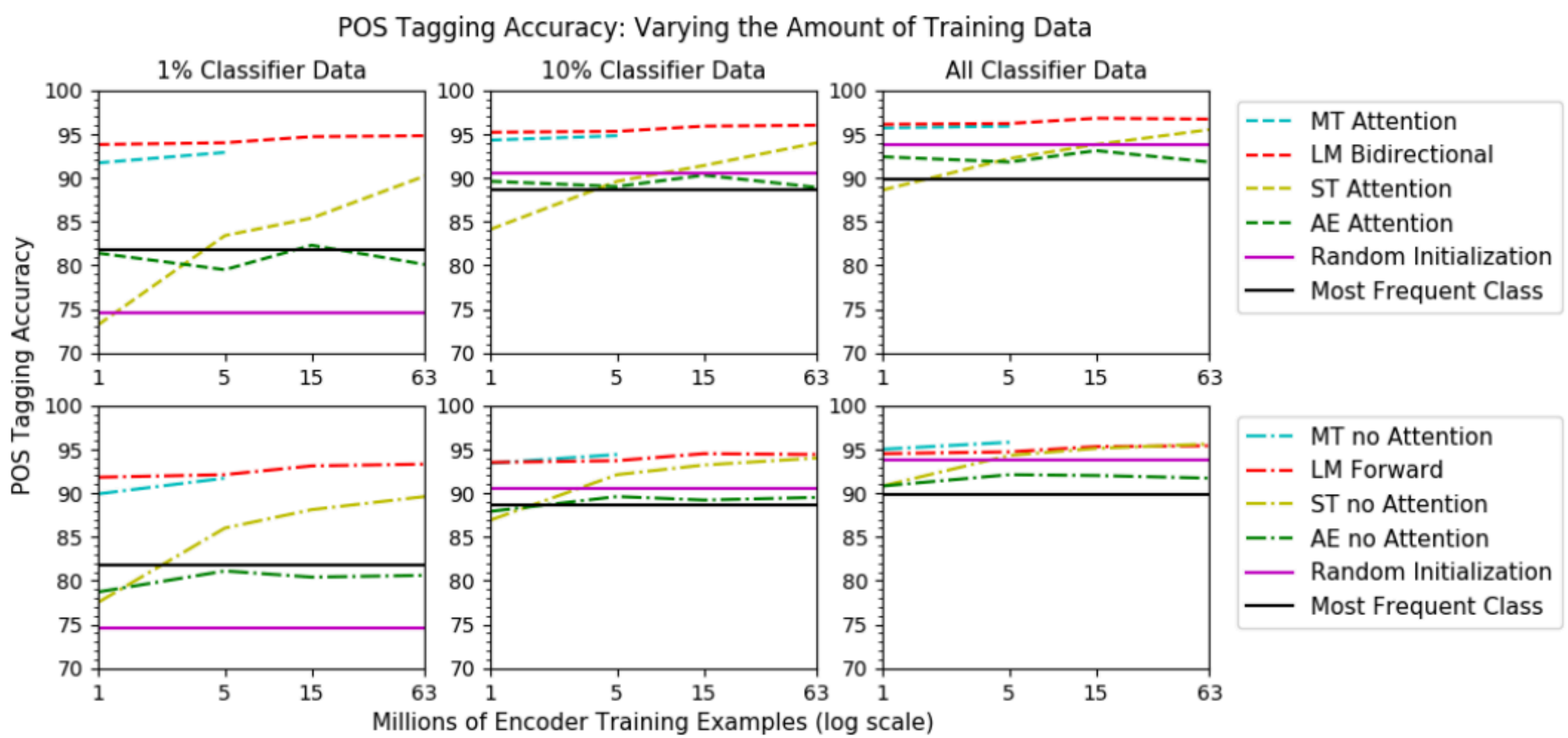

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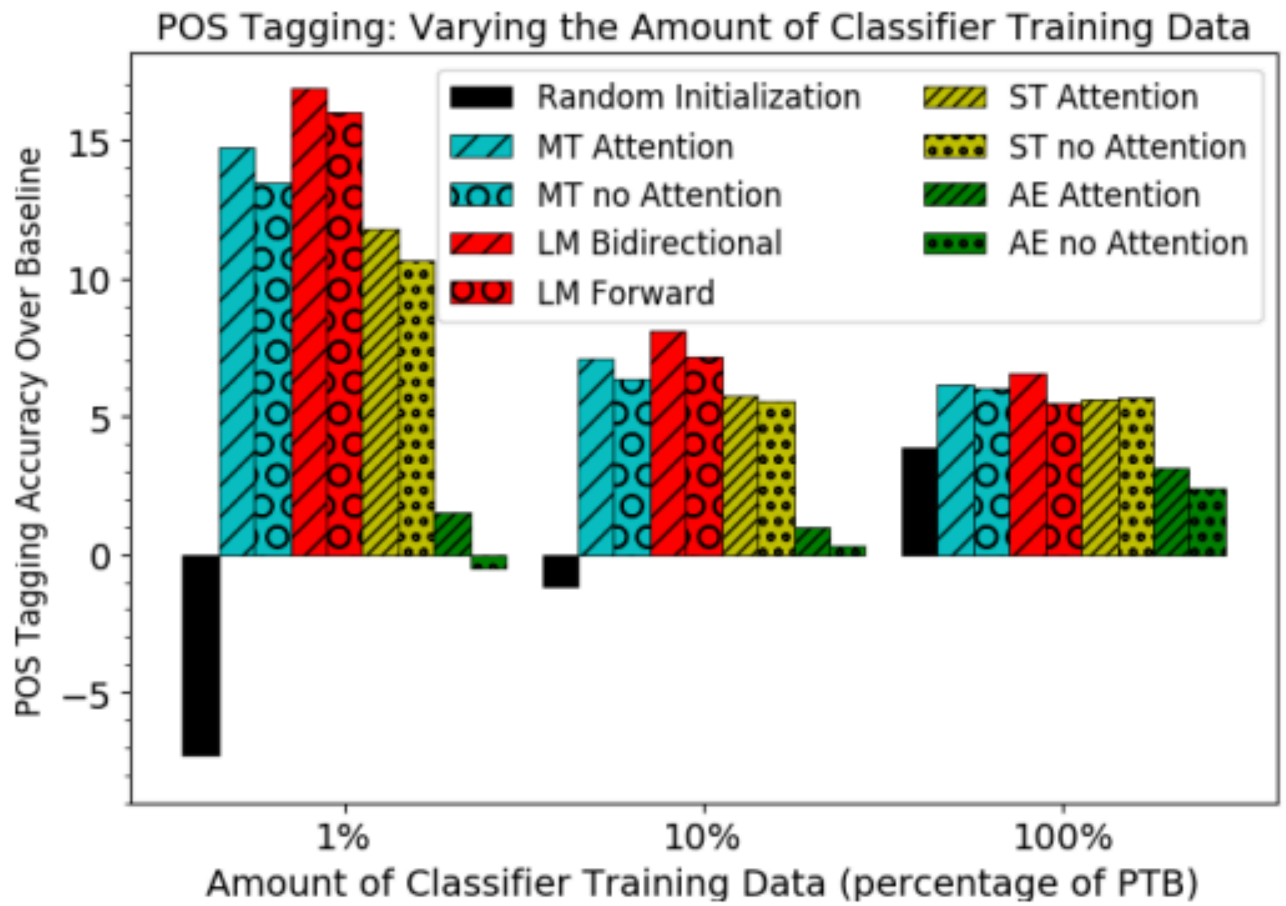


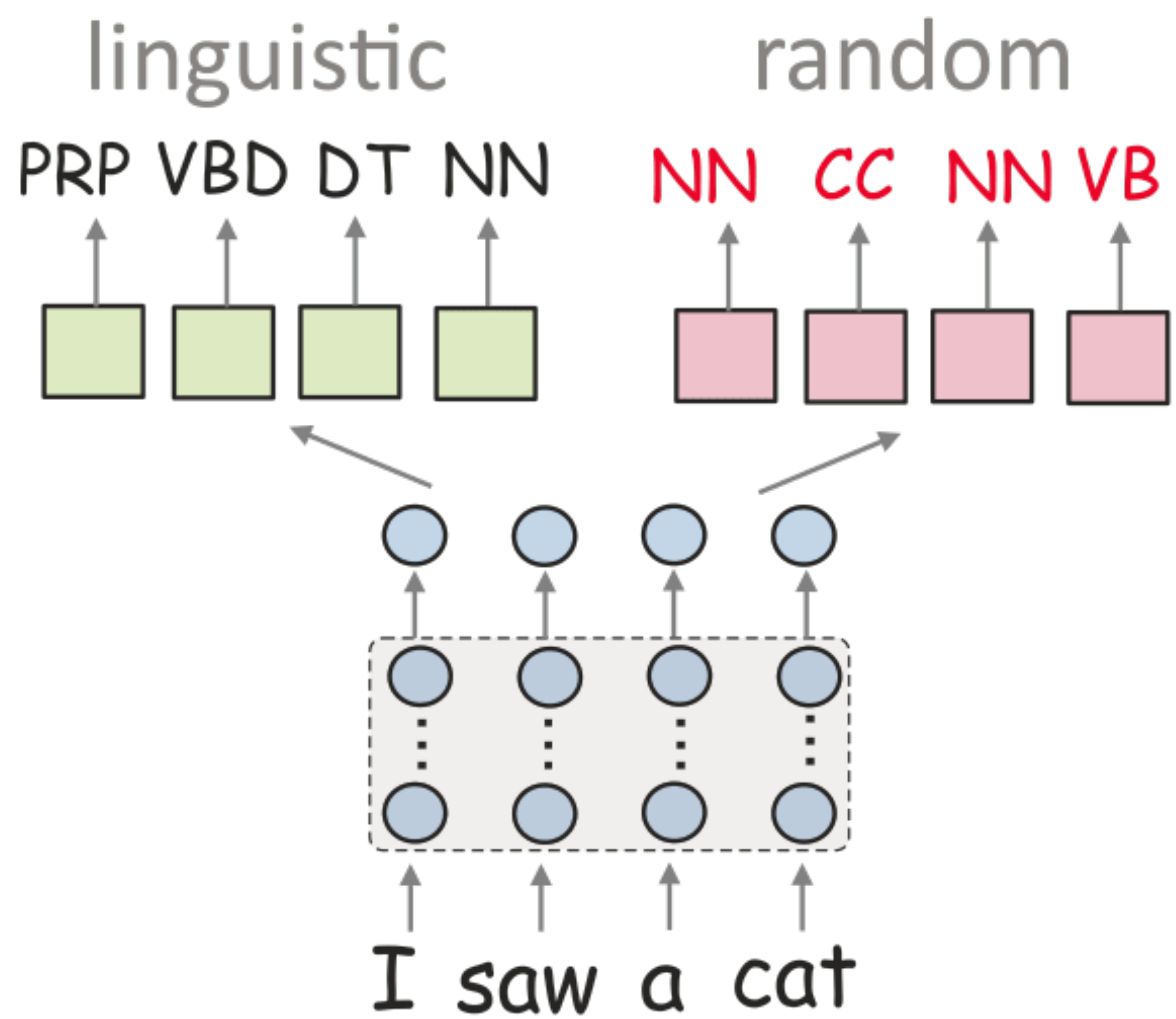
(a) WC-MFC baselines for different amounts of PTB training data: 1% PTB: 81.8%; 10% PTB: 88.6%; 100% PTB: 89.9%.

Zhang, Kelly W., and Samuel R. Bowman. "Language modeling teaches you more syntax than translation does: Lessons learned through auxiliary task analysis." *arXiv preprint arXiv:1809.10040* (2018).

2. Models often perform equally well on tasks with randomly assigned variables.

Hewitt, John, and Percy Liang. "Designing and Interpreting Probes with Control Tasks." arXiv preprint arXiv:1909.03368 (2019).

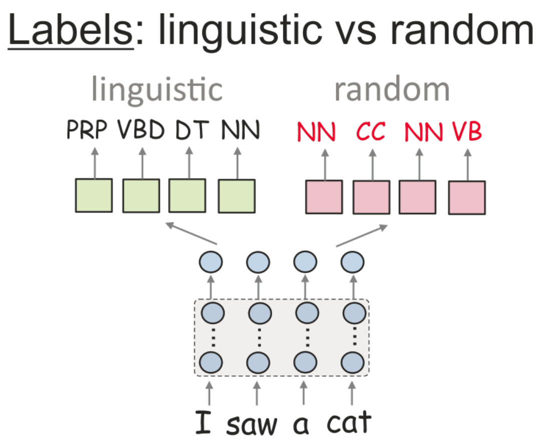
Labels: linguistic vs random



Probe	PoS	Ctl	Select.	Dep	Ctl	Select.
Probes with Default Hyperparameters						
Linear	97.2	71.2	26.0	-	-	-
Bilinear	-	-	-	89.0	82.4	6.6
MLP-1	97.3	92.8	4.5	92.3	93.0	-0.7
MLP-2	97.3	93.2	4.2	93.9	92.0	1.9
Probes with 0.4 Dropout						
Linear	97.1	67.3	29.8	-	-	-
Bilinear	-	-	-	90.4	73.7	16.7
MLP-1	97.5	93.4	4.1	93.8	93.1	0.7
MLP-2	97.4	94.1	3.4	94.7	93.5	1.3
Probes Designed with Control Tasks						
Linear	97.0	64.0	33.0	-	-	-
Bilinear	-	-	-	91.0	83.1	7.9
MLP-1	97.2	80.6	16.6	90.5	84.3	6.2
MLP-2	97.2	81.7	15.4	92.8	89.8	3.0

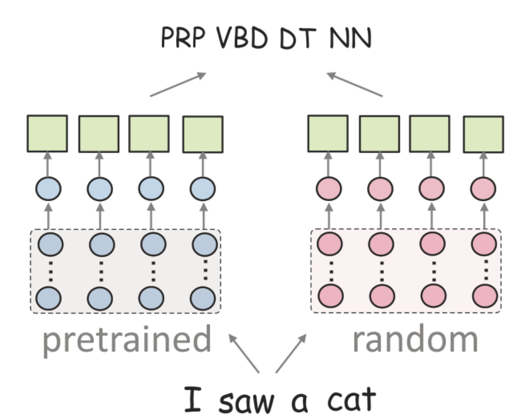
Hewitt, John, and Percy Liang. "Designing and Interpreting Probes with Control Tasks." arXiv preprint arXiv:1909.03368 (2019).

If a random model can solve the linguistic task equally well, what can we say about the model's quality?



If models solve the random task equally well, is there anything we can say about how well the model represents linguistic features?

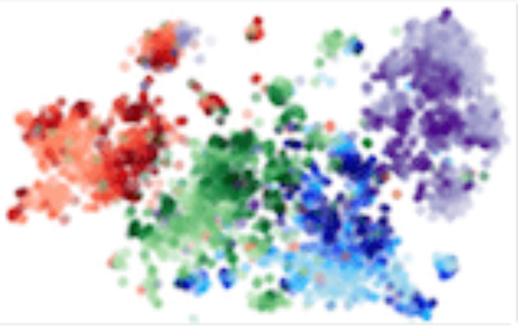
Model: trained vs random



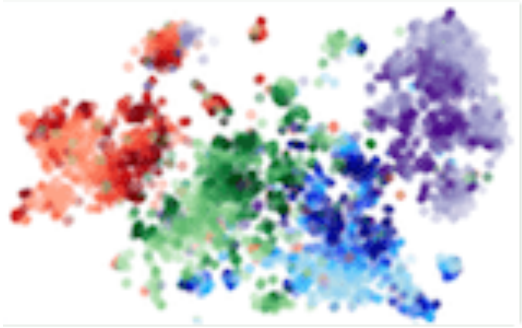
How can we capture how **hard** it is for the probe to learn the task?

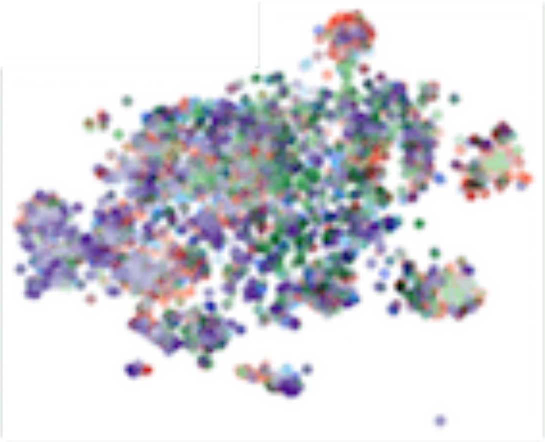
$$\mathcal{D} = \{((x_1, y_1), (x_2, y_2), \ldots (x_n, y_n)\}$$

Representations $x_{1:n}$ and labels $y_{1:n}$.

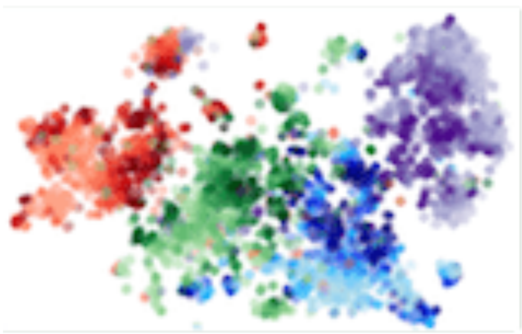


https://lena-voita.github.io/posts/mdl_probes.html

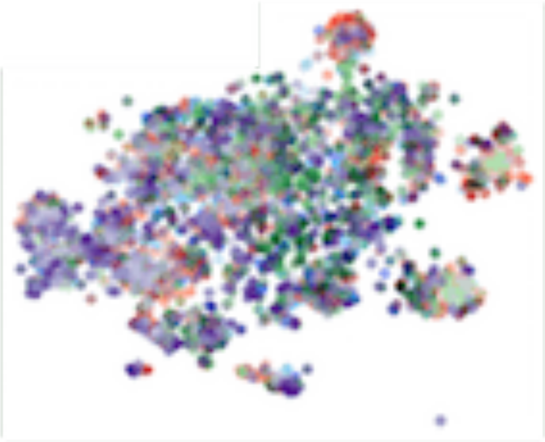




Strong Regularity



Weak Regularity



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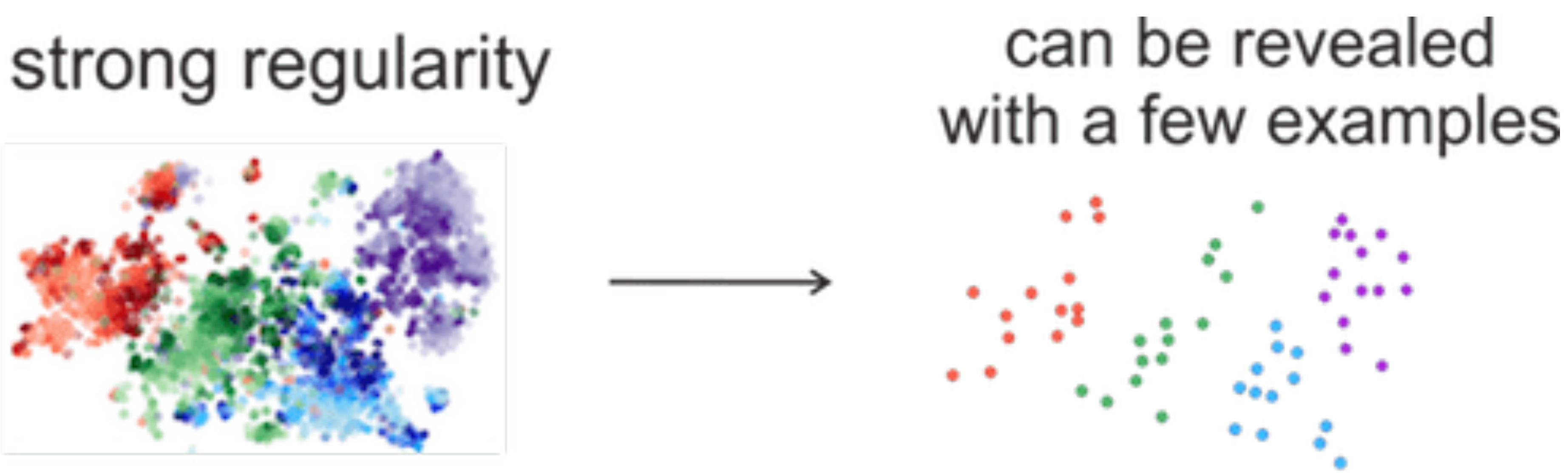

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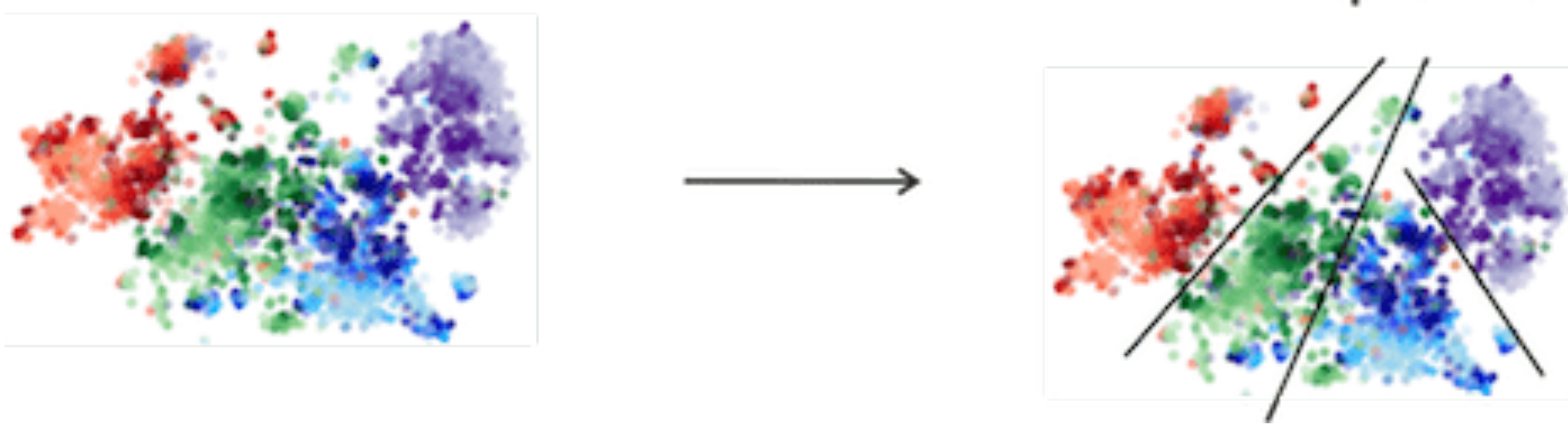
strong regularity

can be explained with a simple "rule"



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Rissanen, Jorma. "Universal coding, information, prediction, and estimation." *IEEE Transactions on Information theory* 30.4 (1984): 629-636.

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1. Send first block with a uniform code.

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1. Send first block with a uniform code.
2. Learn model on the sent block(s).

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1. Send first block with a uniform code.
2. Learn model on the sent block(s).
3. Use model to communicate next block (in a shorter way compared to uniform code.)
4. Repeat until all data is sent.

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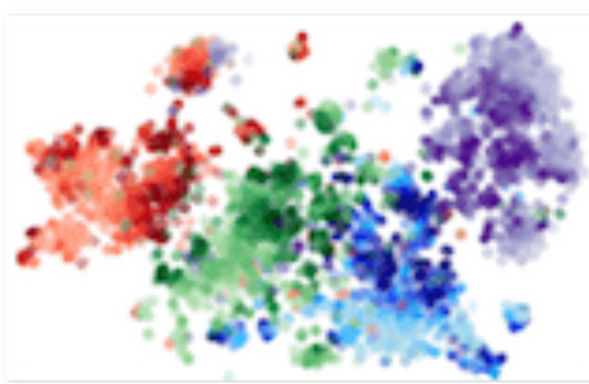
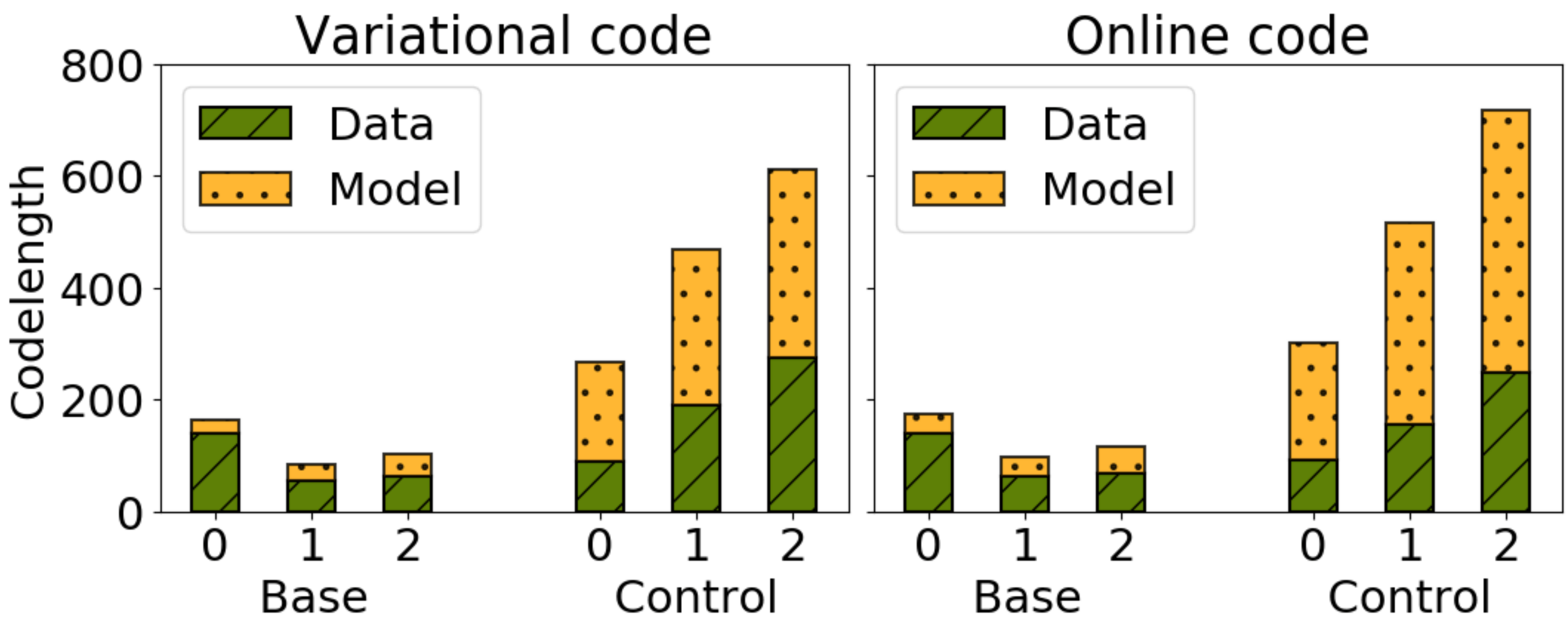
strong regularity



can be revealed
with a few examples

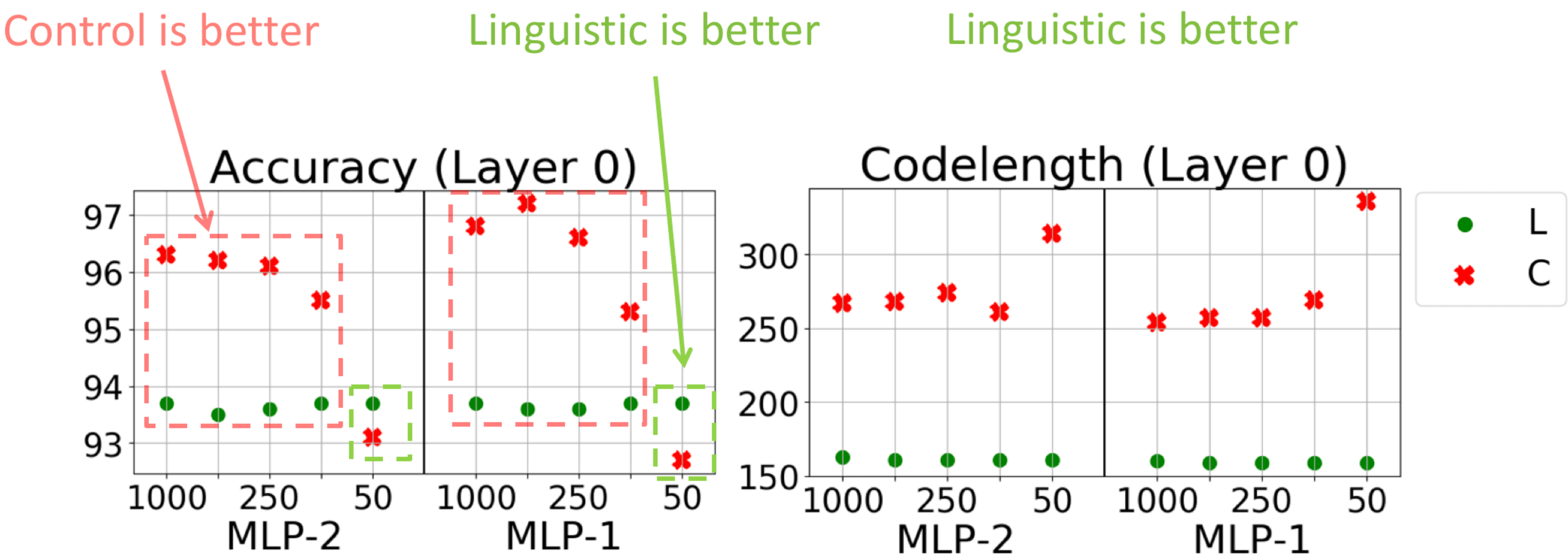
Results

Variational & Online Codes Report Similar Behavior



https://lena-voita.github.io/posts/mdl_probes.html

Across HPs, Accuracy Unclear; MDL Clear

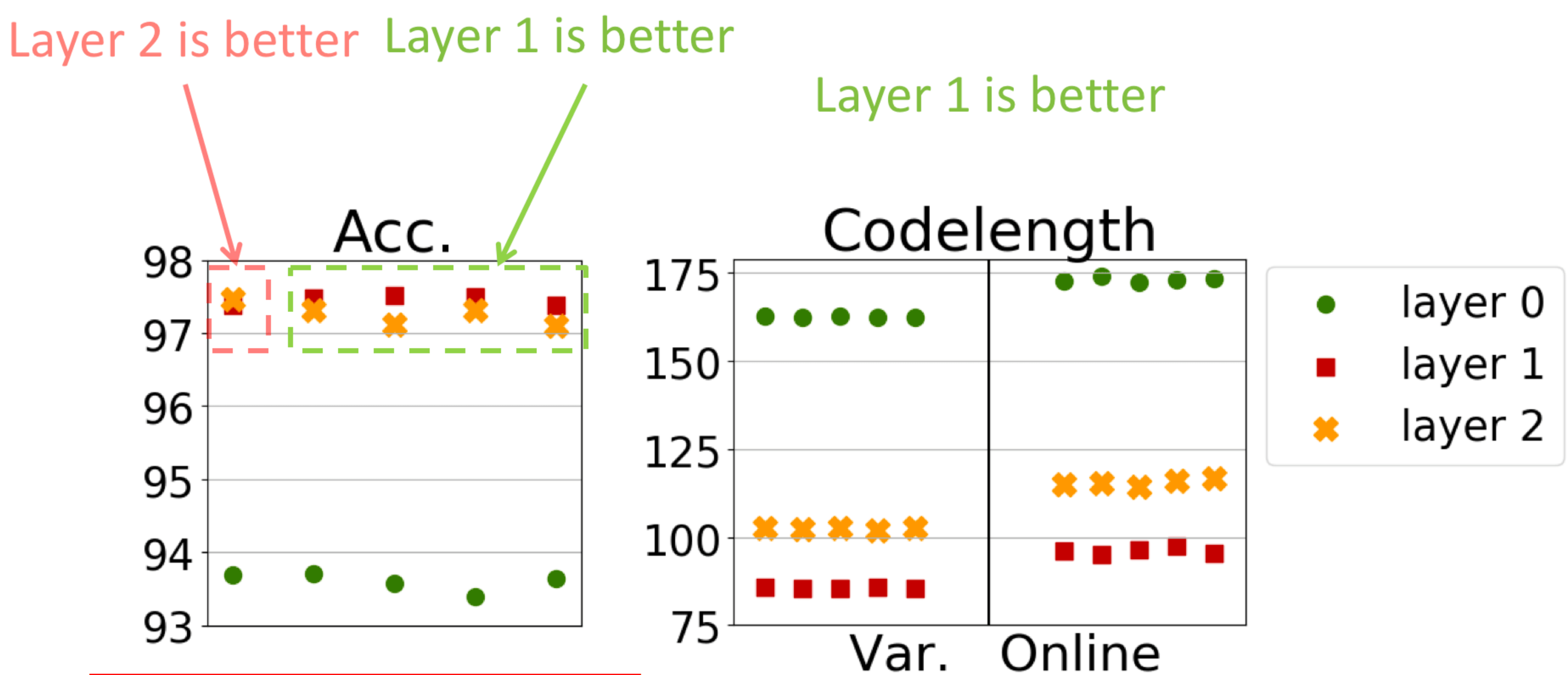


Accuracy is wrong for 8 out of 10 settings, MDL is always correct

(for accuracy higher is better, for codelength – lower)

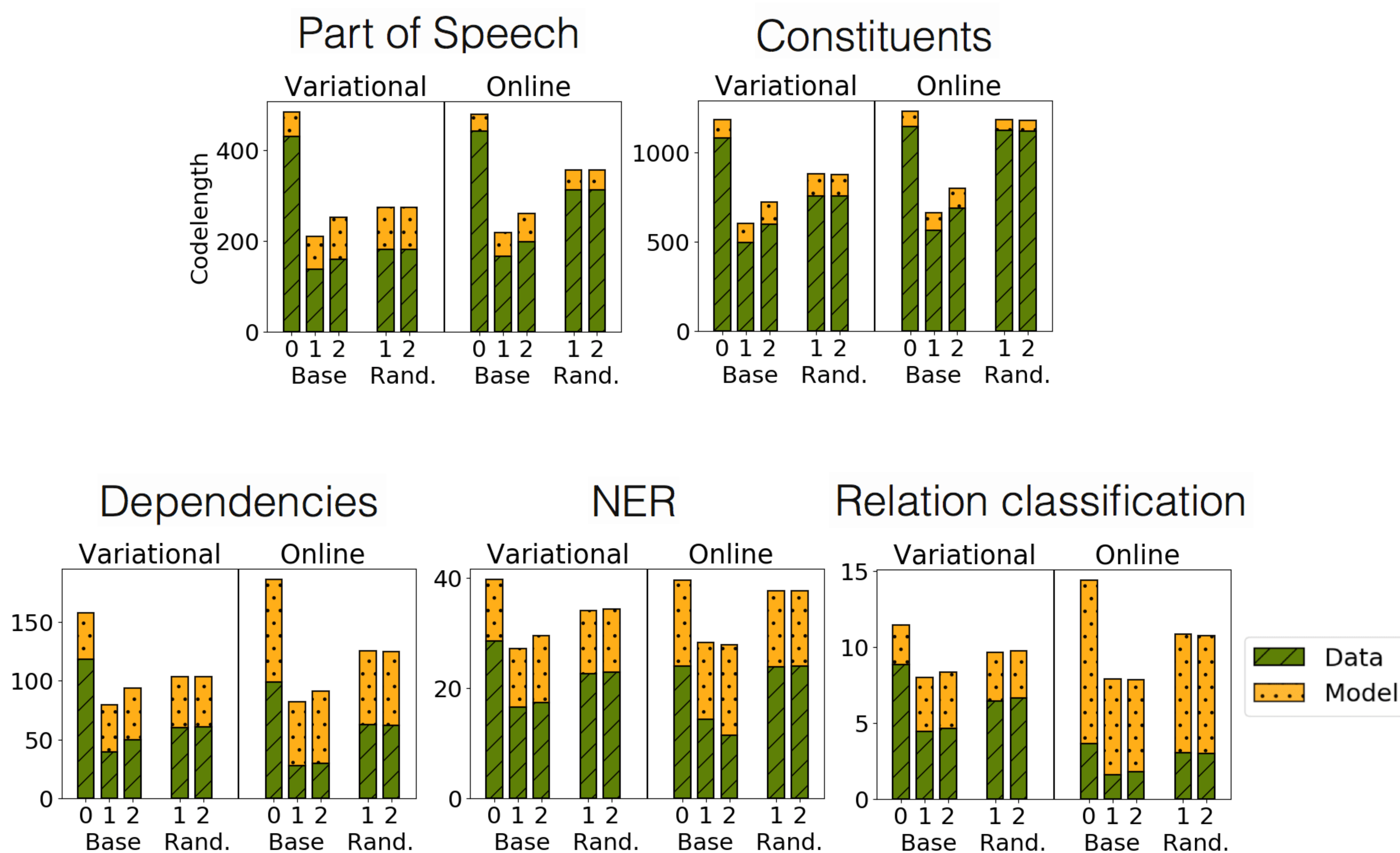
https://lena-voita.github.io/posts/mdl_probes.html

Across Random Seeds, Acc Unstable; MDL Stable



Very close,
results are inconclusive

Well separated


Part of Speech
Constituents
Dependencies
NER
Relation classification
Variational
Online
Codelength
0 1 2
Base
1 2
Rand.
Data
Model

Author Take-Aways

1. Layer 0 vs. Contextual: Even random contextual is better.
2. Code-lengths for randomly initialized models are higher.
3. Randomly initialized layers don't evolve.

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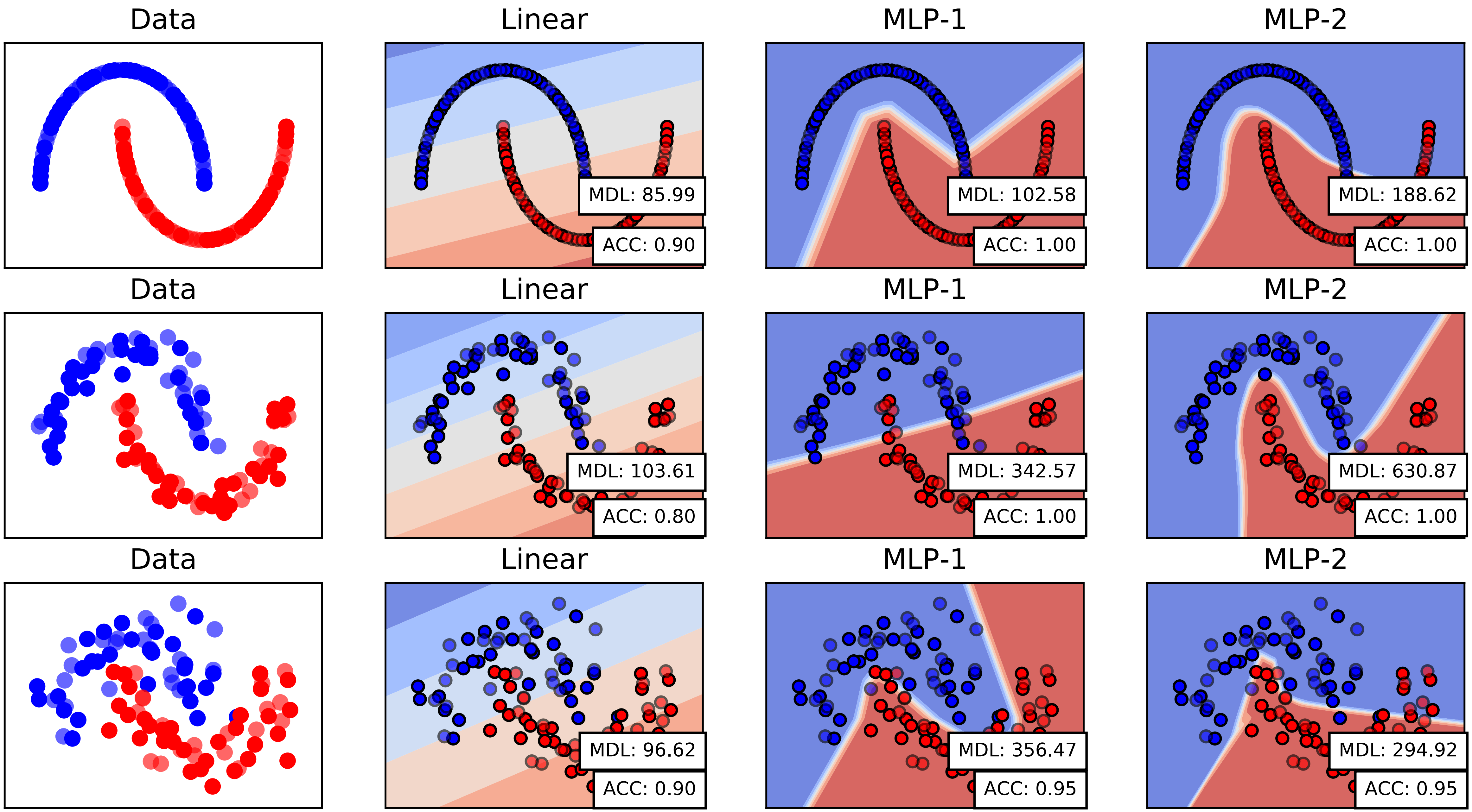
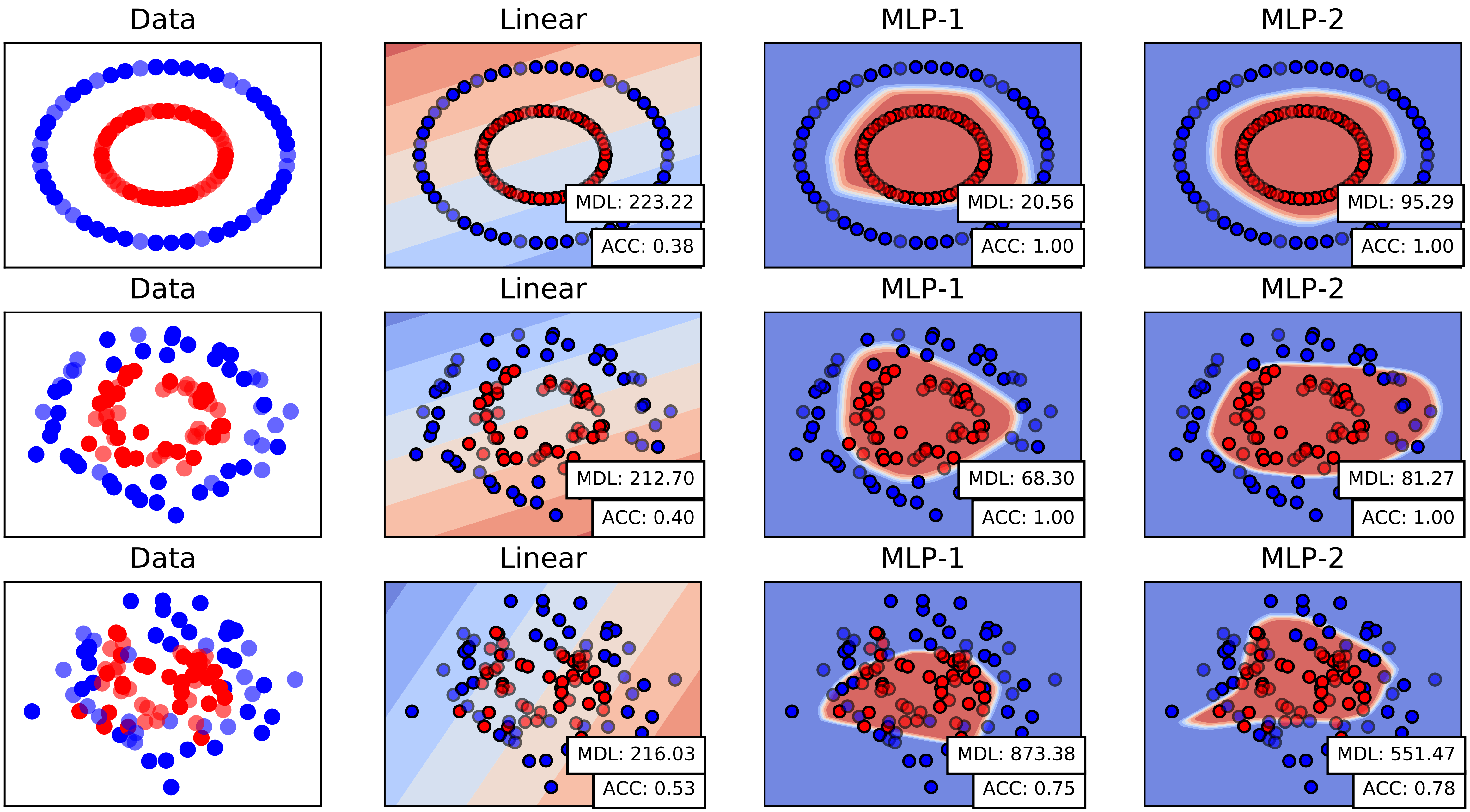
My Take-Aways

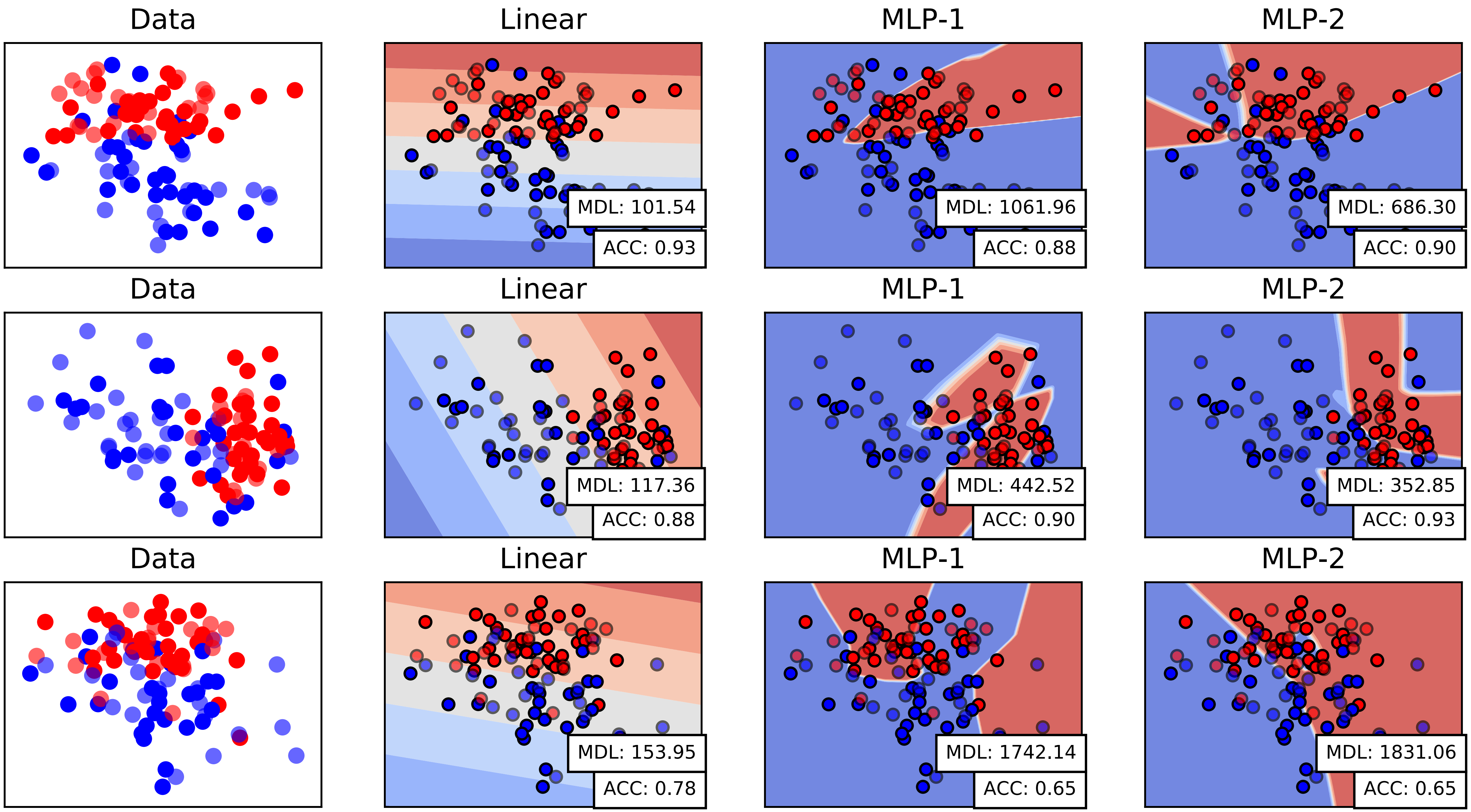
1. Seems better than accuracy.
2. Seems not that much better and requires accuracy for context.
    1. The HPs that “failed” for accuracy were very small.
    2. The separation across random seeds for MDL shows a difference, but we can’t readily interpret that difference.

Small Experiments
For Building Intuition

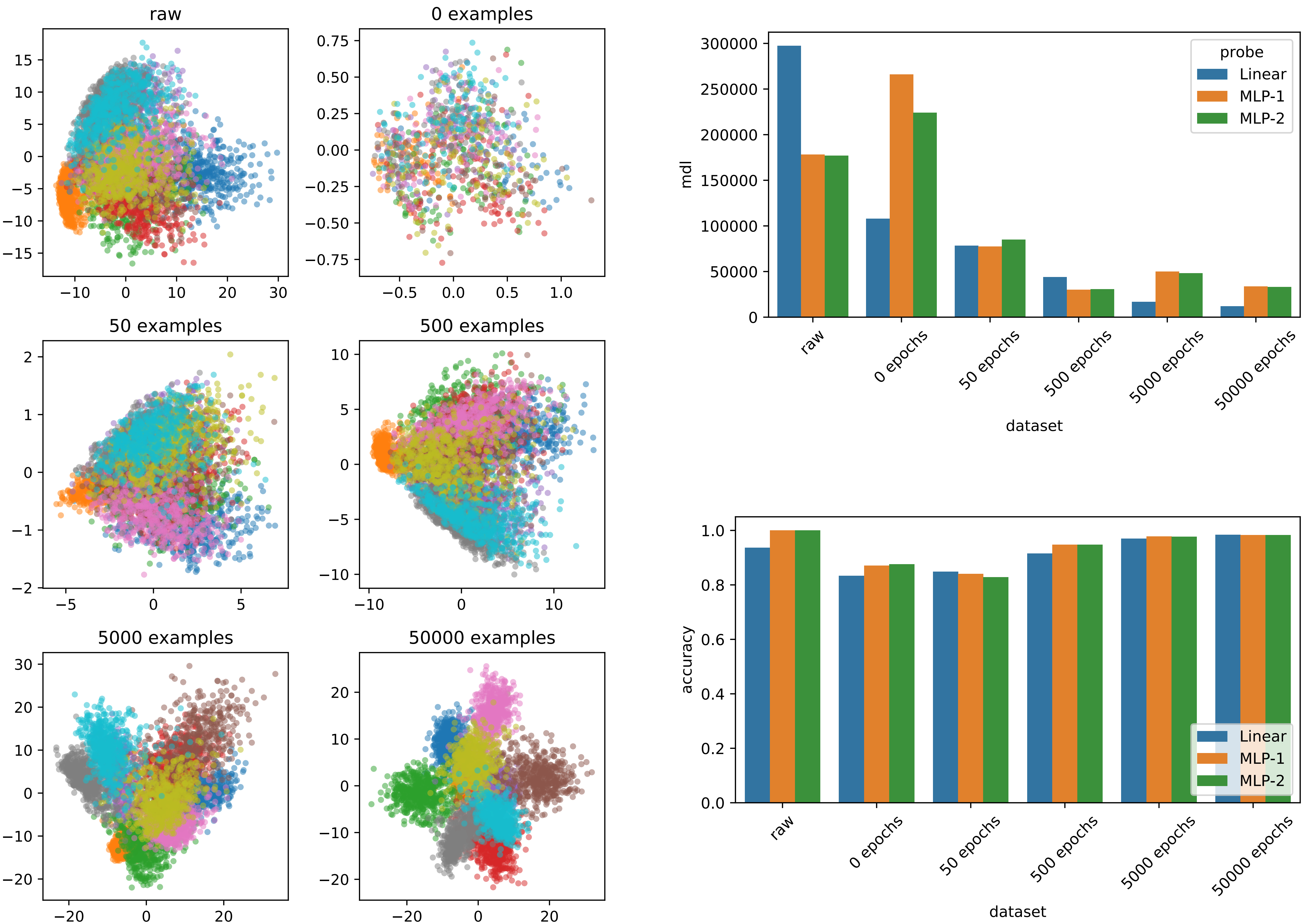

Data
Linear
MLP-1
MLP-2
MDL: 85.99
ACC: 0.90
MDL: 102.58
ACC: 1.00
MDL: 188.62
ACC: 1.00
Data
Linear
MLP-1
MLP-2
MDL: 103.61
ACC: 0.80
MDL: 342.57
ACC: 1.00
MDL: 630.87
ACC: 1.00
Data
Linear
MLP-1
MLP-2
MDL: 96.62
ACC: 0.90
MDL: 356.47
ACC: 0.95
MDL: 294.92
ACC: 0.95



Data
Linear
MDL: 223.22
ACC: 0.38
MLP-1
MDL: 20.56
ACC: 1.00
MLP-2
MDL: 95.29
ACC: 1.00
Data
Linear
MDL: 212.70
ACC: 0.40
MLP-1
MDL: 68.30
ACC: 1.00
MLP-2
MDL: 81.27
ACC: 1.00
Data
Linear
MDL: 216.03
ACC: 0.53
MLP-1
MDL: 873.38
ACC: 0.75
MLP-2
MDL: 551.47
ACC: 0.78



Data
Linear
MDL: 101.54
ACC: 0.93
MLP-1
MDL: 1061.96
ACC: 0.88
MLP-2
MDL: 686.30
ACC: 0.90
Data
Linear
MDL: 117.36
ACC: 0.88
MLP-1
MDL: 442.52
ACC: 0.90
MLP-2
MDL: 352.85
ACC: 0.93
Data
Linear
MDL: 153.95
ACC: 0.78
MLP-1
MDL: 1742.14
ACC: 0.65
MLP-2
MDL: 1831.06
ACC: 0.65


raw
0 examples
50 examples
500 examples
5000 examples
50000 examples
mdl
accuracy
probe
Linear
MLP-1
MLP-2
raw
0 epochs
50 epochs
500 epochs
5000 epochs
50000 epochs
dataset