CS11-711 Advanced NLP

Debugging and Understanding NLP Models

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w/ Some Slides by Danish Pruthi

A Typical Situation

- You’ve implemented an NLP system based on neural networks
- You’ve looked at the code, and it looks OK
- It has low accuracy, or makes incomprehensible errors
- **What do I do?**

Three Model Understanding Dimensions

- **Debugging Implementation:** Identifying problems in your implementation (or assumptions)
- **Actionable Evaluation:** Identifying typical error cases and understanding how to fix them
- **Interpreting Predictions:** Examining individual predictions to dig deeper

Debugging

In Neural Net Models, Debugging is Paramount!

- Models are often **complicated and opaque**
- **Everything is a hyperparameter** (network size, model variations, batch size/strategy, optimizer/ learning rate)
- Non-convex, stochastic optimization has **no guarantee of decreasing/converging loss**

Possible Causes

- **Training time problems**
  - Lack of model capacity
  - Poor training algorithm
  - Training time bug
- **Test time problems**
  - Disconnect between training and test
  - Failure of search algorithm
- **Overfitting**
- **Mismatch between optimized function and eval**

Don't debug all at once! Start top and work down.

Debugging at Training Time

Identifying Training Time Problems

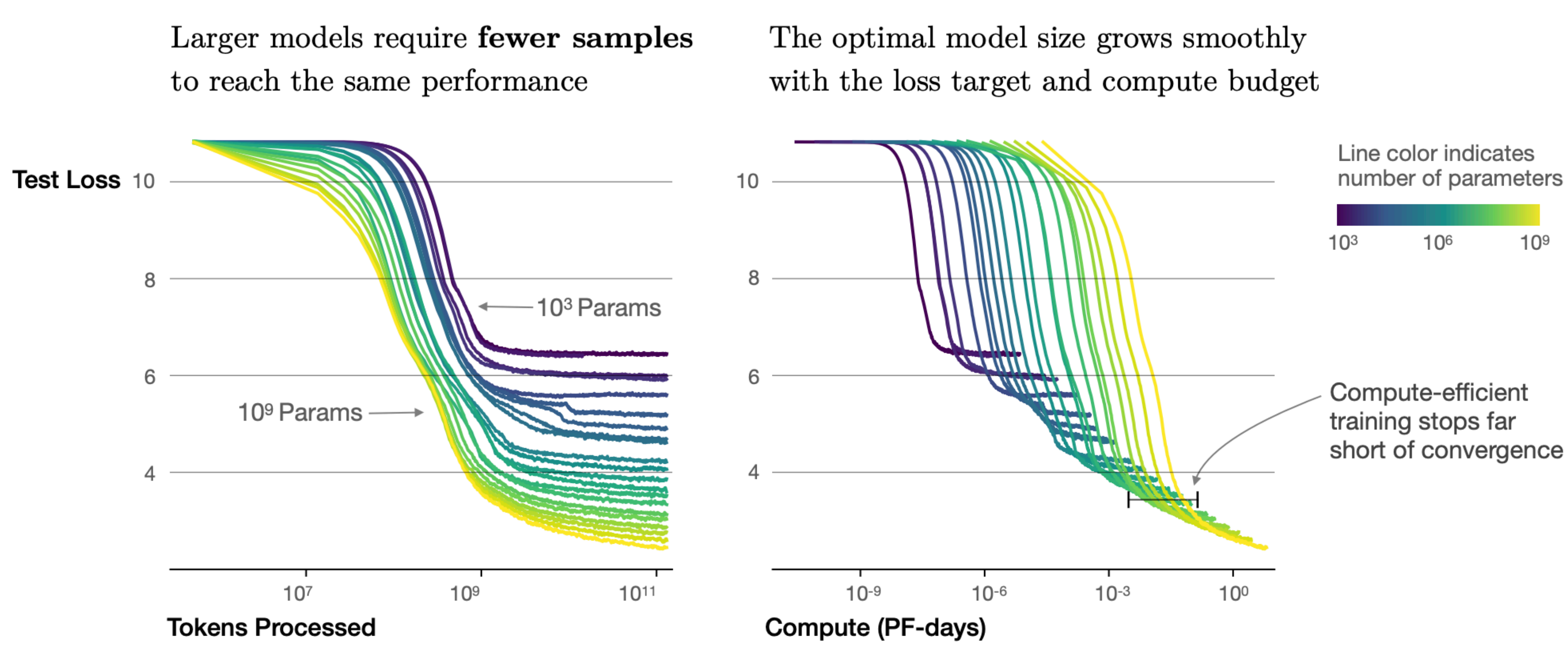
- Look at the **loss function** calculated on the **training set**
  - Is the loss function going down?
  - Is it going down basically to zero if you run training long enough (e.g. 20-30 epochs)?
  - If not, does it go down to zero if you use very small datasets?

Is My Model Too Weak?

- Larger models tend to perform better, esp. when pre-trained (e.g. Raffel et al. 2020)

Model	GLUE Average	CoLA Matthew's	SST-2 Accuracy	MRPC F1	MRPC Accuracy	STS-B Pearson	STS-B Spearman
Previous best	89.4[a]	69.2[b]	97.1[a]	**93.6**[b]	**91.5**[b]	92.7[b]	92.3[b]
T5-Small	77.4	41.0	91.8	89.7	86.6	85.6	85.0
T5-Base	82.7	51.1	95.2	90.7	87.5	89.4	88.6
T5-Large	86.4	61.2	96.3	92.4	89.9	89.9	89.2
T5-3B	88.5	67.1	97.4	92.5	90.0	90.6	89.8
T5-11B	**90.3**	**71.6**	**97.5**	92.8	90.4	**93.1**	**92.8**

- Larger models can learn with fewer steps (Kaplan et al. 2020, Li et al. 2020)



Trouble w/ Optimization

- If increasing model size doesn’t help, you may have an optimization problem
- Check your
  - **optimizer** (Adam? standard SGD?)
  - **learning rate** (is the rate you're using standard, are you using decay?)
  - **initialization** (uniform? Glorot?)
  - **minibatching** (are you using sufficiently large batches?)
- Pay attention to these details when replicating previous work

Debugging at Test Time

Training/Test Disconnects

- Usually your loss calculation and prediction will be implemented in different functions
- Especially true for structured prediction models (e.g. encoder-decoders)
- Like all software engineering: **duplicated code is a source of bugs**!
- Also, usually loss calculation is minibatched, generation not.

Debugging Minibatching

- Debugging mini-batched loss calculation
  - Calculate loss with **large batch size** (e.g. 32)
  - Calculate loss for **each sentence individually and sum**
  - The values should be the same (modulo numerical precision)
- Create a unit test that tests this!

Debugging Structured Generation

- Your decoding code should get the same score as loss calculation
- Test this:
  - Call **decoding function**, to generate an output, and keep track of its score
  - Call **loss function** on the generated output
  - The score of the two functions should be the same
- Create a unit test doing this!

Debugging Search

- As you make search better, the **model score** should get better (almost all the time)
- Search w/ varying beam sizes and make sure you get a better overall model score with larger sizes
- Create a unit test testing this!

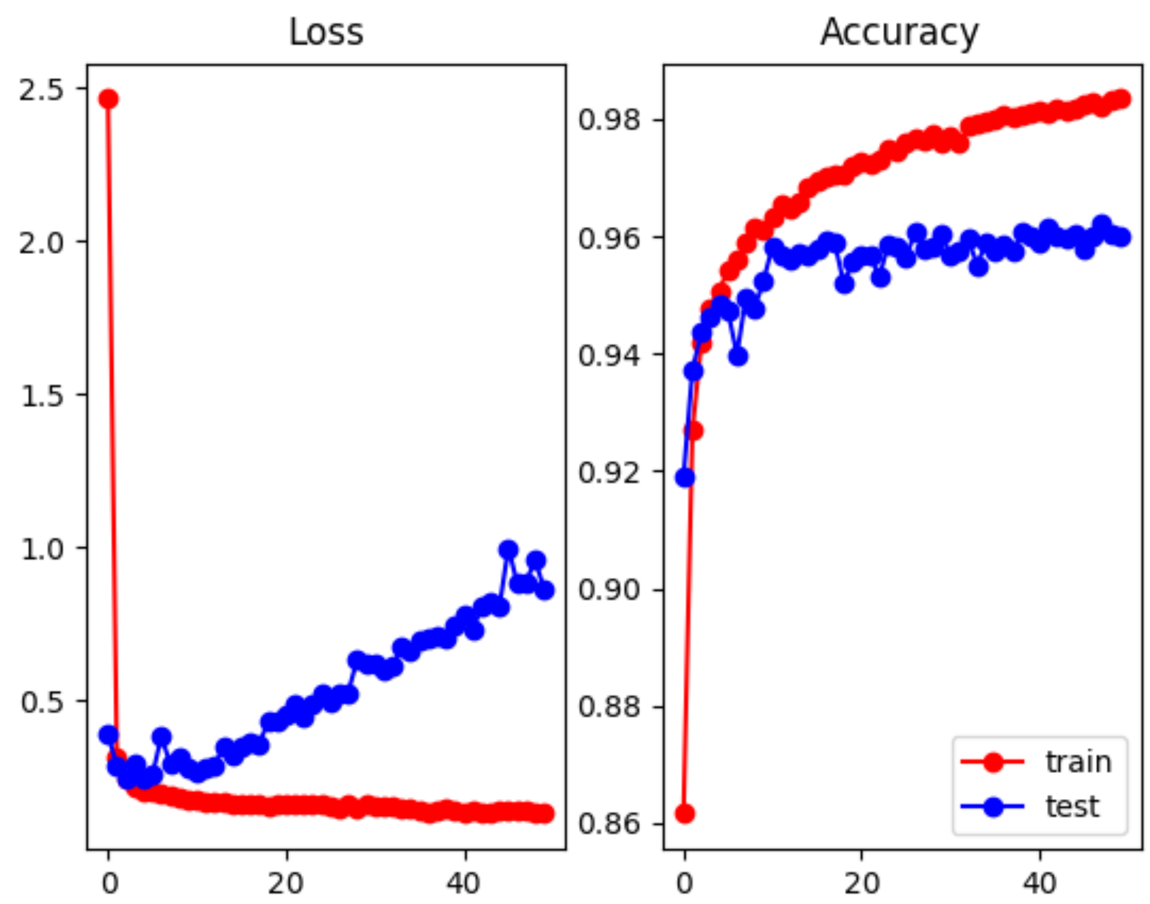
Mismatch b/t Optimized Function and Evaluation Metric

Loss Function, Evaluation Metric

- It is very common to optimize for maximum likelihood for training
- But even though likelihood is getting better, accuracy can get worse

Example w/ Classification

- Loss and accuracy are de-correlated (see dev)

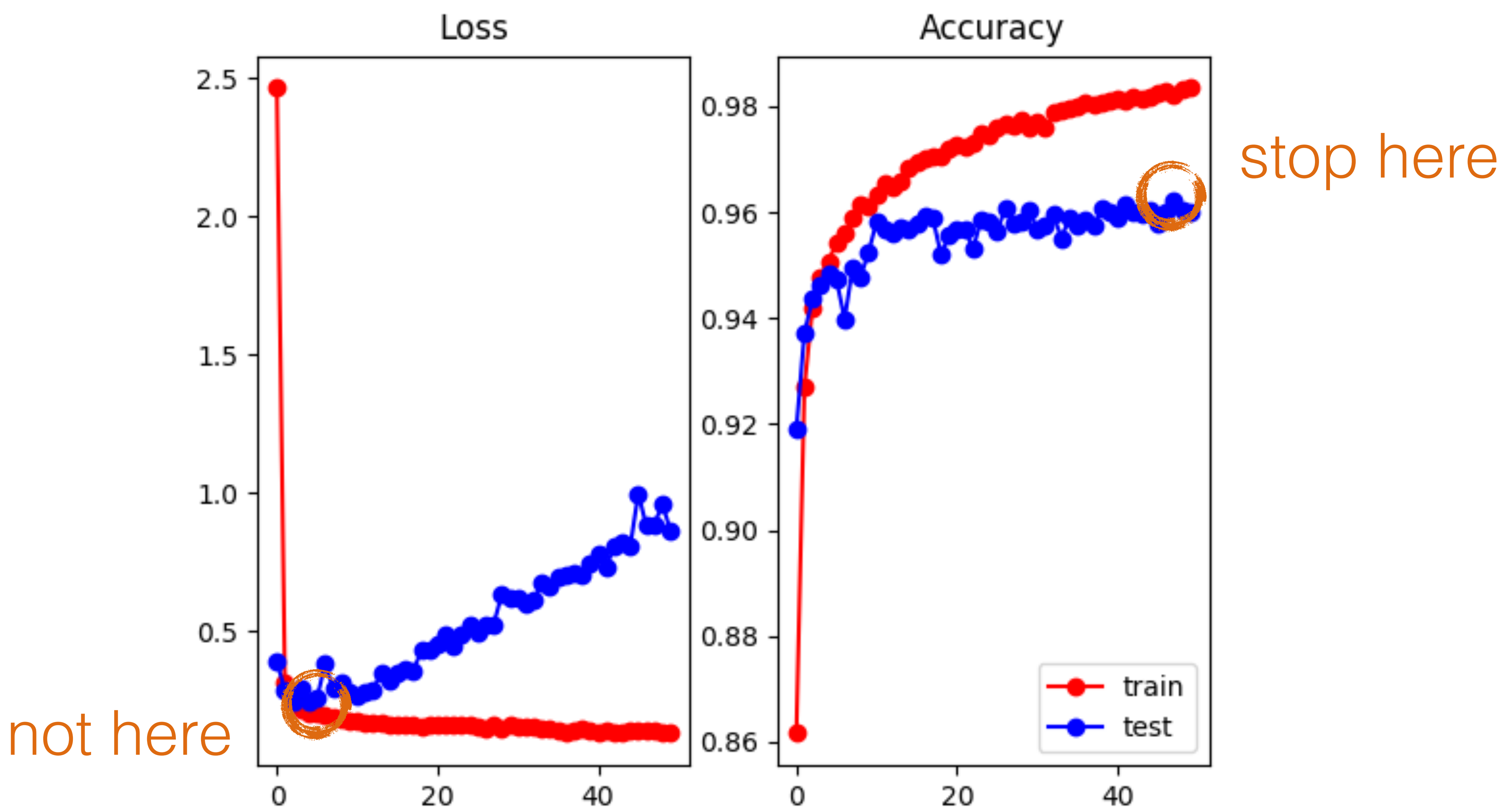


- Why? Model gets more confident about its mistakes.

Managing Loss Function/ Eval Metric Differences

- Most principled way: use structured prediction techniques to be discussed in future classes
    - Structured max-margin training
    - Minimum risk training
    - Reinforcement learning
    - Reward augmented maximum likelihood

A Simple Method:
Early Stopping w/ Eval Metric



Actionable Evaluation

Look At Your Data!

- Both bugs and research directions can be found by **looking at your model outputs**

- Your model is repeating all the time
  > I thought it was bad bad bad bad bad bad bad
  → need a new inference algorithm?

- The model is consistently failing on named entities
  → need a better model of named entities?

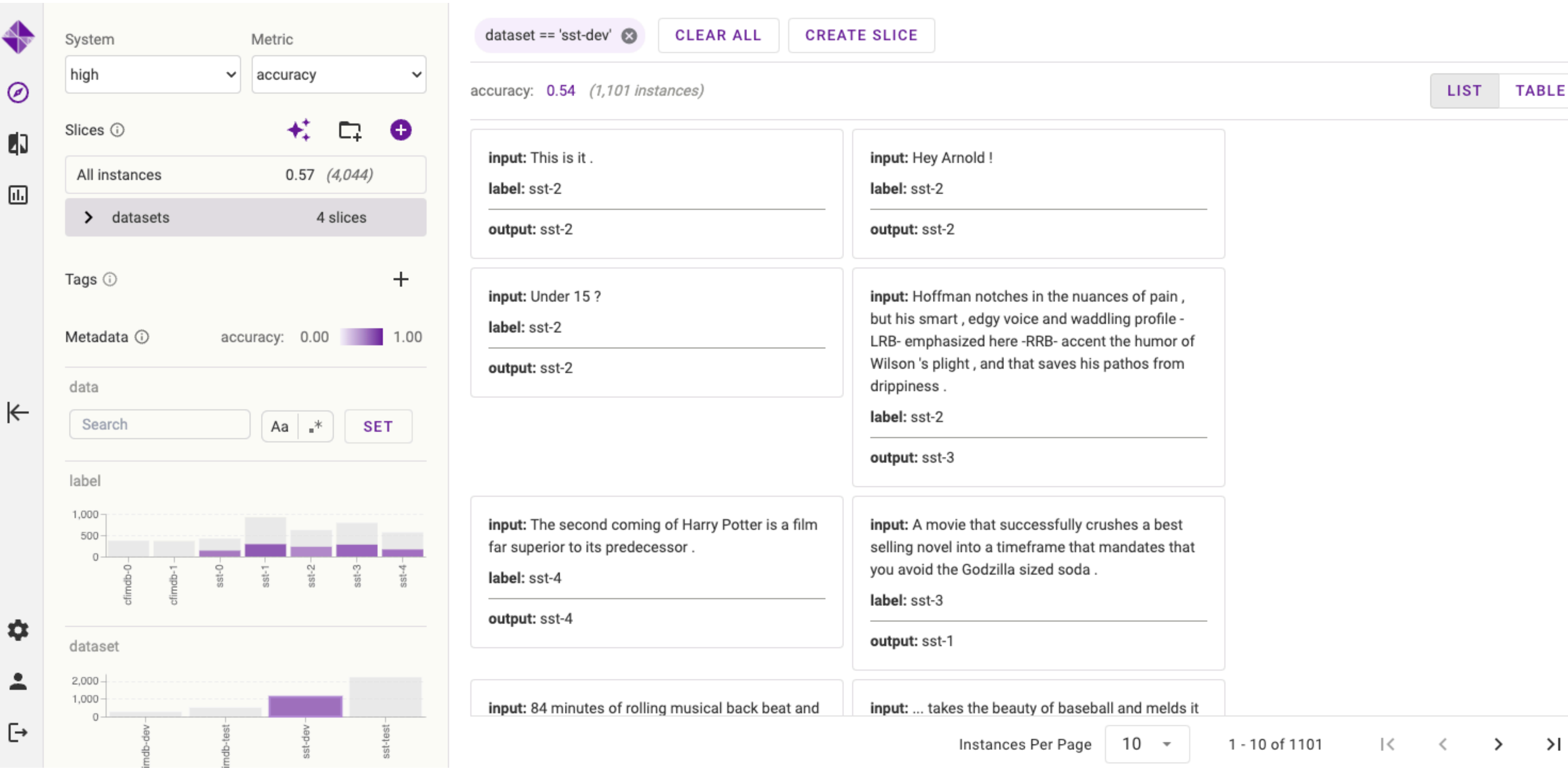
Which Data to Look At?

- Random examples
- Low-scoring examples (low `eval(y)`)
- Comparatively low examples (low `eval(y_1) - eval(y_2)`)

Slicing

- Create a subset of your examples where you expect one model to do better than others
  - Long sentences
  - Sentences that contain a word
  - Sentences that belong to a cluster
  - etc. etc.

Example: Zeno



http://zenoml.com

Interpretation of Predictions and Model Internals

Why Interpret Model Predictions?

- e.g. You want to know
    - **which words were used** in making a decision to verify its accuracy.
    - whether your model has learned a difficult pattern, or is focused on **spurious correlations**.
    - understand what information a **pre-trained model has captured** internally.

LIME: Local Perturbations

For	Christmas	Song	visit	my	channel!	;)	prob	weight
1	0	1	1	0	0	1	0.17	0.57
0	1	1	1	1	0	1	0.17	0.71
1	0	0	1	1	1	1	0.99	0.71
1	0	1	1	1	1	1	0.99	0.86
0	1	1	1	0	0	1	0.17	0.57

label_prob	feature	feature_weight
0.9939024	channel!	6.180747
0.9939024	For	0.000000
0.9939024	;)	0.000000

Ribeiro et al, KDD 2016 https://christophm.github.io/interpretable-ml-book/lime.html

Explanation Technique: Gradient-based Scores

Method	Attribution $R_i^c(x)$
Gradient * Input	$x_i \cdot \dfrac{\partial S_c(x)}{\partial x_i}$
Integrated Gradient	$(x_i - \bar{x_i}) \cdot \displaystyle\int_{\alpha=0}^{1} \dfrac{\partial S_c(\tilde{x})}{\partial(\tilde{x_i})}\Bigg\vert_{\tilde{x}=\bar{x}+\alpha(x-\bar{x})} d\alpha$
<u>ϵ-LRP</u>	$x_i \cdot \dfrac{\partial^g S_c(x)}{\partial x_i}, \quad g = \dfrac{f(z)}{z}$
<u>DeepLIFT</u>	$(x_i - \bar{x_i}) \cdot \dfrac{\partial^g S_c(x)}{\partial x_i}, \quad g = \dfrac{f(z) - f(\bar{z})}{z - \bar{z}}$

Example of attributions on MNIST

ReLU | Tanh | Sigmoid | Softplus

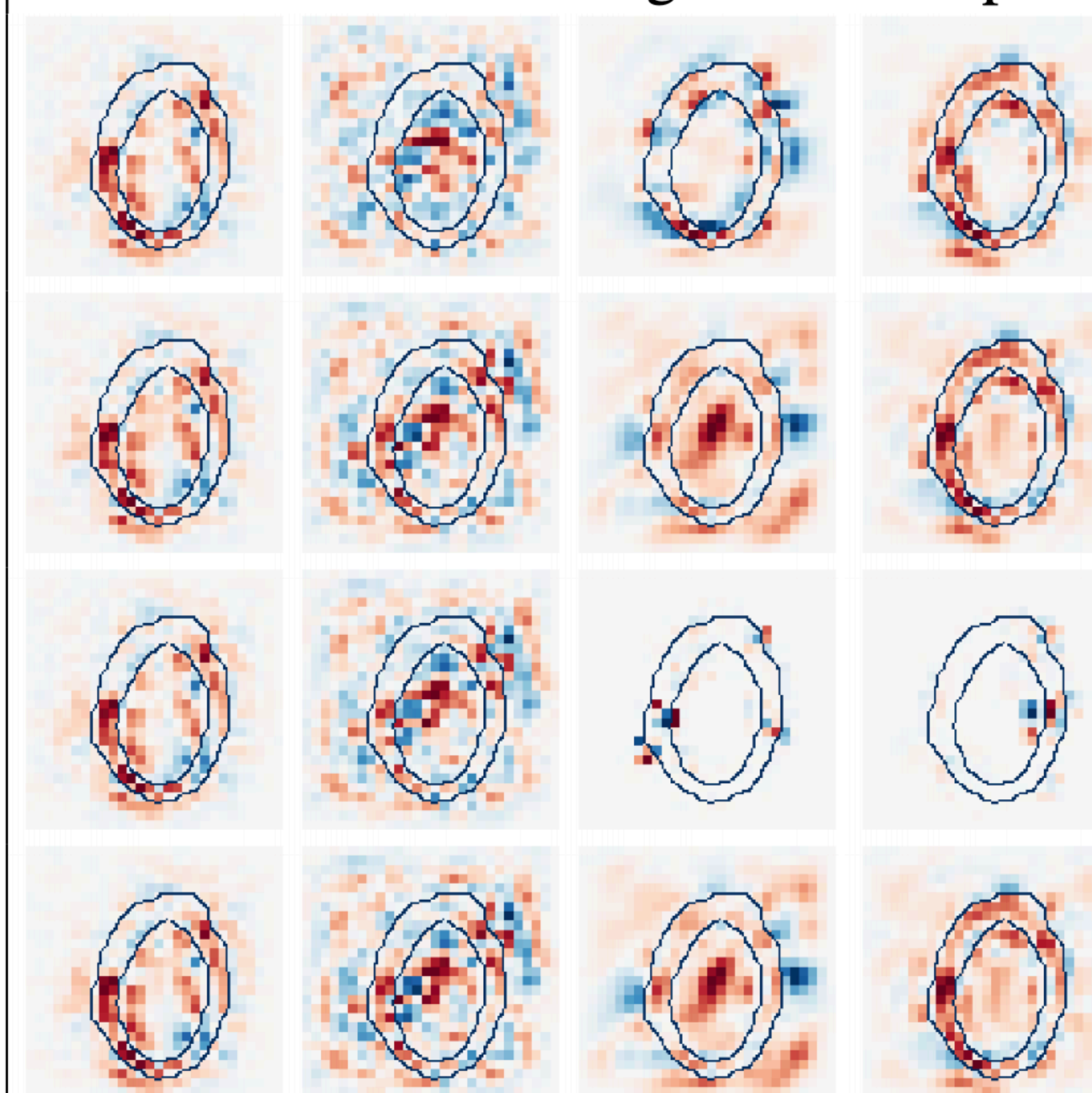
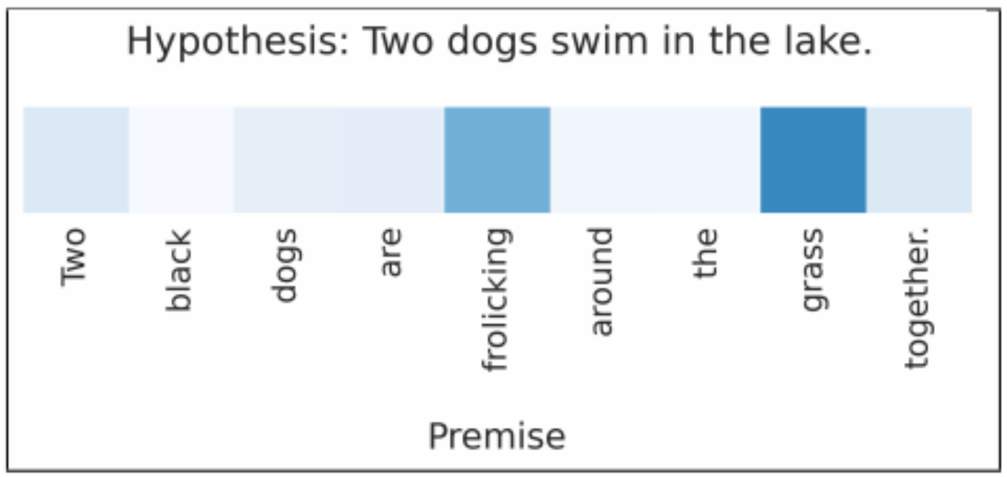


Figure from Ancona et al, ICLR 2018

Explanation Technique: Attention

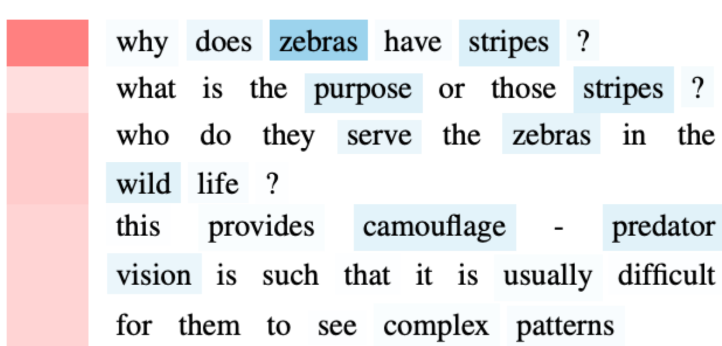


Entailment

Rocktäschel et al, 2015

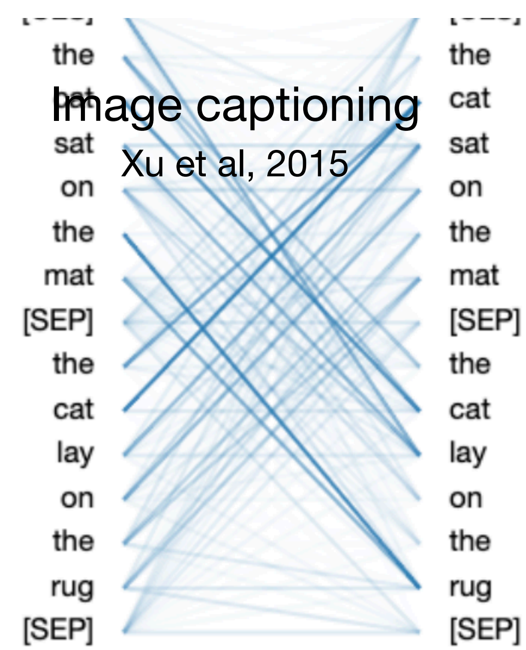
Image captioning

Xu et al, 2015



Document classification

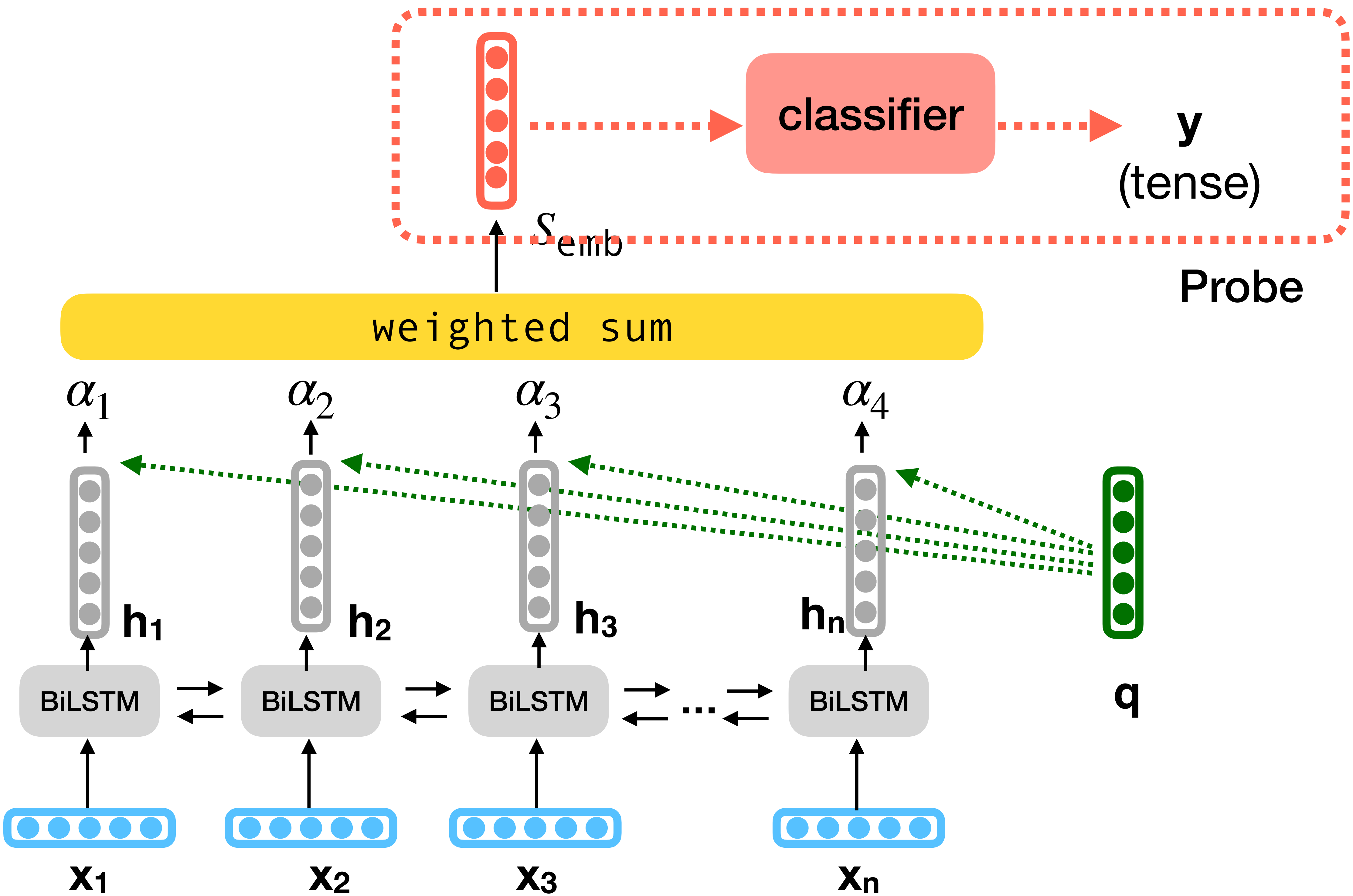
Yang et al, 2016



BERTViz

Vig et al, 2019

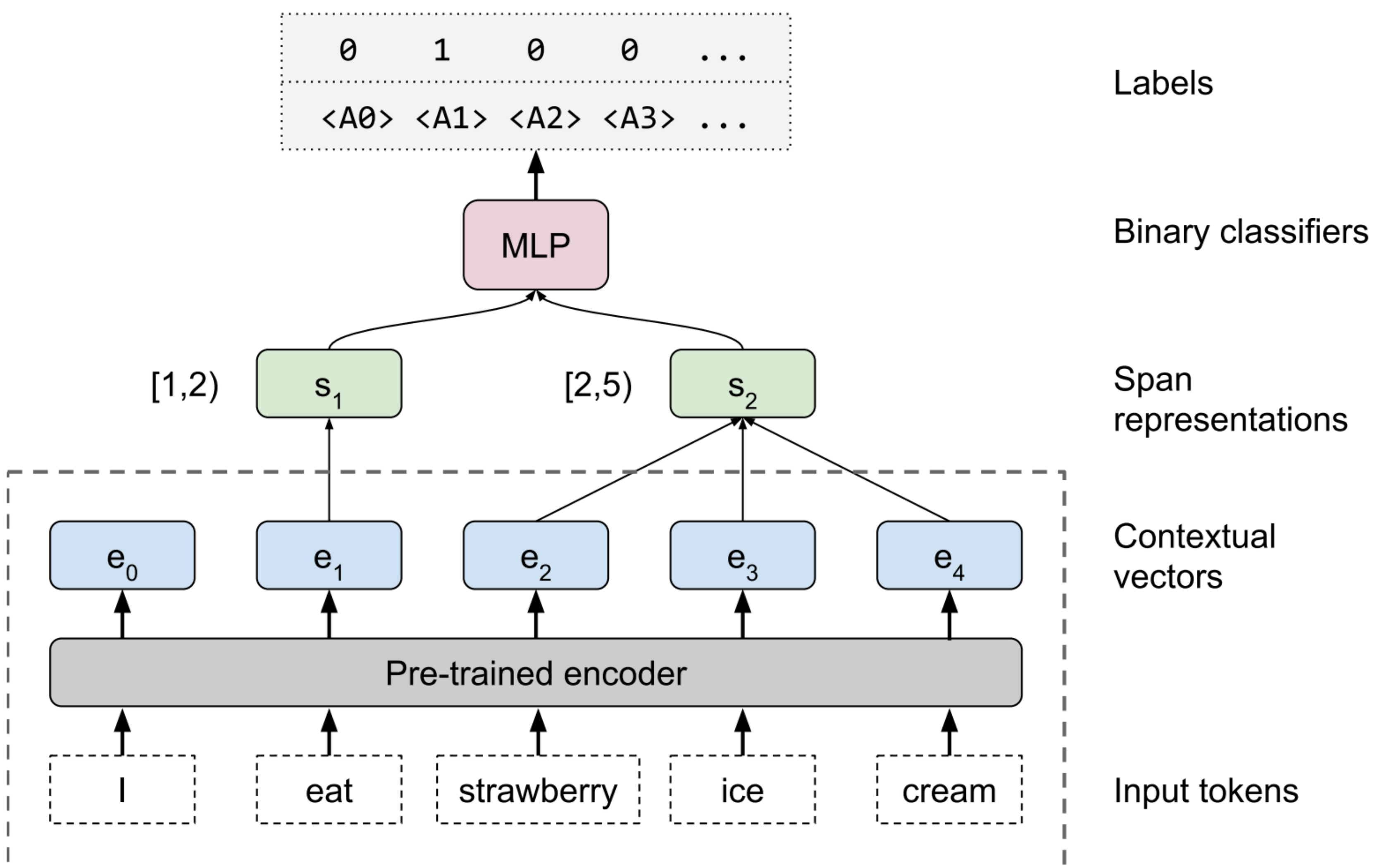
Probing



classifier
y
(tense)
s_{emb}
Probe
weighted sum
α_1
α_2
α_3
α_4
h1
h2
h3
hn
q
BiLSTM
BiLSTM
BiLSTM
BiLSTM
...
x1
x2
x3
xn

Edge Probing
(Tenney et al. 2019)

- A general framework that allows for probing of many types of information



Issues with probing

- Did I interpret the representation or my probing classifier learn the task itself (Hewitt et al. 2019)
  - Solution - information theoretic probing that controls for classifier complexity (Voita et al. 2020)
- Can only probe for properties you have supervision for
- Correlation doesn't imply causation
- and more…

Probing Classifiers: Promises, Shortcomings, and Alternatives
by Yonatan Belinkov

Questions?