Lecture 7

Predicting Structured Outputs

Part 1: Interlude: What Are Structured Outputs

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Predicting Structured Outputs





So far, we've studied this scenario:

- Structured inputs
- Familiar unstructured outputs: classification / regression.



In the next part of class, we study **structured outputs**.



Reminder: Kinds of Structure





Sequence

Grid



Graph









Hierarchy

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What is $|\mathcal{Y}|$?

Recap: Logistic Regression and Perceptron Losses

The two losses we've seen for multi-class classification: (changing notation slightly)

$$L_{LR}(y) = -\log \Pr(Y = y|x) = -\operatorname{score}(y) + \log \sum_{y' \in \mathcal{Y}} \exp(\operatorname{score}(y'))$$
$$= -\operatorname{score}(y) + \max_{y' \in \mathcal{Y}} \operatorname{score}(y')$$

For classification:

- we had $\mathcal{Y} = \{1, 2, ..., K\}$
- the model (linear or NN) outputs a vector *a* of scores for each class, so score(y) = a_y.

Can we generalize this to structured \mathcal{Y} ?

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Part 2: Probabilistic Models of Structures

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Probabilistic Models of Structures

Our model must be able to assign a score to every possible structure, $score(y; x, \theta)$. For brevity we just write score(y), but remember it depends on input and params.

From this, we can get a probability distribution over possible structures:

$$\Pr(y \mid x) = \frac{\exp(\text{score}(y))}{\sum_{y' \in \mathcal{Y}} \exp(\text{score}(y'))}$$



Modelling challenges

Essential computational prerequisites:

- score(y)
- for prediction: $\arg \max_{y \in \mathcal{Y}} \operatorname{score}(y)$
- for learning: $\log \sum_{y \in \mathcal{Y}} \exp(\operatorname{score}(y))$

The challenges: unlike multi-class classification,

- \mathcal{Y} can vary for each data point (e.g., with n. horses)
- $|\mathcal{Y}|$ can get very large: we can't just for-loop over it.

Generally intractable!

But, for certain structures and scoring functions, efficient algorithms exist.

The Road Ahead

In the rest of the class, we shall cover a wide range of structured output tasks:

- Sequence labelling
- Sequence segmentation
- Alignments between sequences;
- Assignments and permutations
- Grid / graph labelling

While there is no general-purpose structure prediction algorithm, we shall learn three main tools that will get you far:

- Dynamic programming
- Integer linear programming
- Gibbs sampling