Language Technologies Institute

Carnegie Mellon University

Algorithms for NLP

CS 11-711 · Fall 2020

Lecture 3: Nonlinear text classification

Emma Strubell

Announcements

- **Project 1: Text classification** will be available after class today, **due Friday September 25**
- Han will lead recitation this Friday to introduce Project 1, and cover environment setup (Python, Jupyter, NumPy, PyTorch).

Recap

Representing text as a bag of words

- Given a text $\boldsymbol{w} = (w_1, w_2, \ldots, w_T) \in \mathcal{V}^*$
- Choose a label $y \in \mathcal{Y}$
- The **bag-of-words** is a fixed-length vector of word counts:

$\boldsymbol{w}$ = The drinks were strong but the fish tacos were bland

$\boldsymbol{x}$ =

0	…	1	1	…	1	…	0	1	2	1	…	2	…	0
aardvark	…	bland	but	…	fish	…	taco	tacos	the	strong	…	were	…	zyther

- Length of $\boldsymbol{x}$ is equal to the size of the vocabulary, V

Recap

Linear classification on bag-of-words

- Let $\psi(\boldsymbol{x}, y)$ score the compatibility of bag-of-words $\boldsymbol{x}$ and label y. Then:

$$\hat{y} = \underset{y}{\text{argmax}}\, \psi(\boldsymbol{x}, y).$$

- In a **linear classifier** this scoring function has the simple form:

$$\psi(\boldsymbol{x}, y) = \boldsymbol{\theta} \cdot \boldsymbol{f}(\boldsymbol{x}, y) = \sum_{j=1} \theta_j \times f_j(\boldsymbol{x}, y),$$

where $\boldsymbol{\theta}$ is a vector of weights, and $\boldsymbol{f}$ is a **feature function**

Recap

Feature functions

- In classification, the feature function is usually a simple combination of $\boldsymbol{x}$ and y, such as:

$$f_j(\boldsymbol{x}, y) = \begin{cases} x_{\text{bland}} & \text{if } y = \text{negative} \\ 0 & \text{otherwise} \end{cases}$$

- If we have K labels, this corresponds to column vectors that look like:

$\boldsymbol{f}(\boldsymbol{x}, y = 1) =$

x_0	x_1	...	$x_{\lvert V\rvert}$	0	0	0	0	0	0	0	0	0	...	0

T

$(K-1) \times V$

$\boldsymbol{f}(\boldsymbol{x}, y = 2) =$

0	0	0	...	0	x_0	x_1	...	$x_{\lvert V\rvert}$	0	0	0	0	...	0

T

V $\quad$ $(K-2) \times V$

$\boldsymbol{f}(\boldsymbol{x}, y = K) =$

0	0	0	0	0	0	0	0	0	...	0	x_0	x_1	...	$x_{\lvert V\rvert}$

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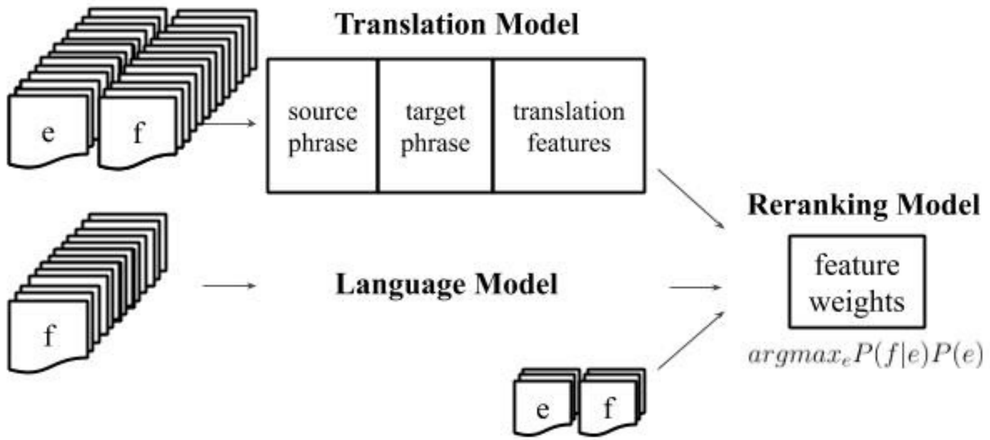
- All these methods for **supervised learning** assume a labeled dataset of N examples:

$$\{(\boldsymbol{x}^{(i)}, y^{(i)})\}_{i=1}^{N}$$

Today

Nonlinear classification & evaluating classifiers

Engineered features



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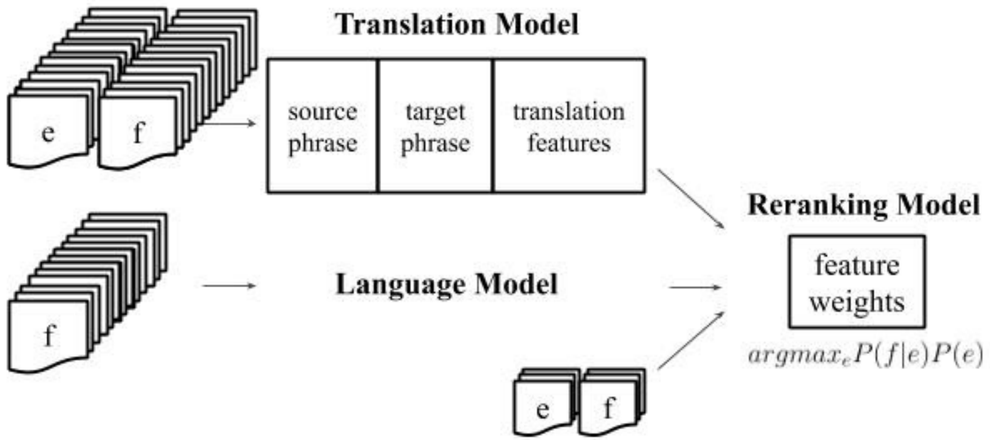

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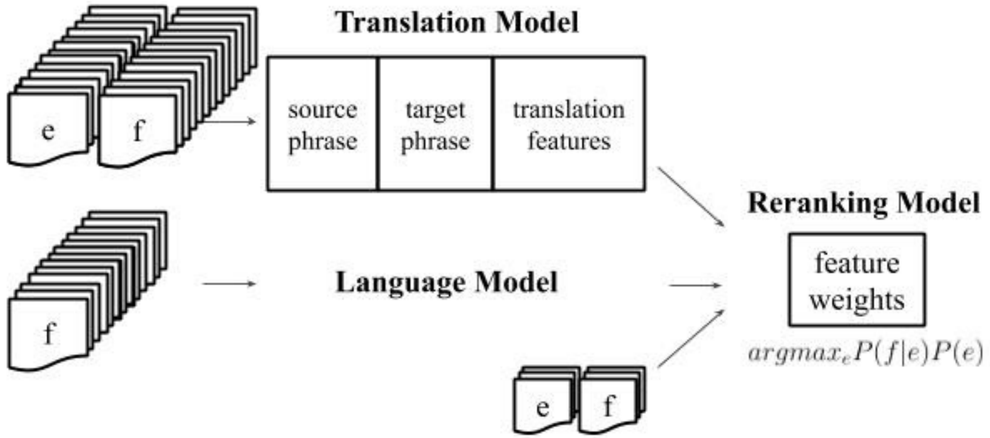

~mid 2010s

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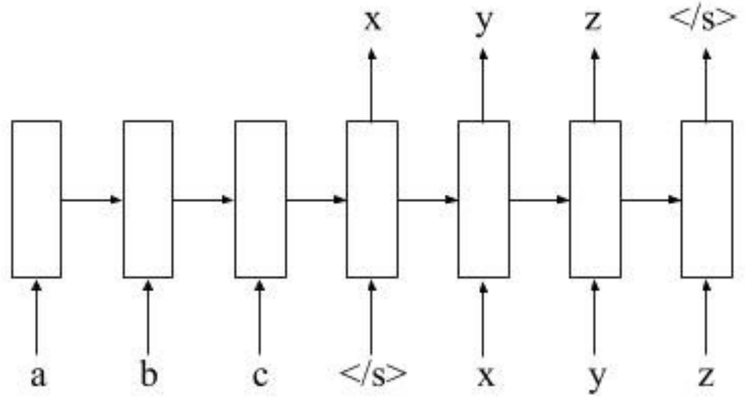

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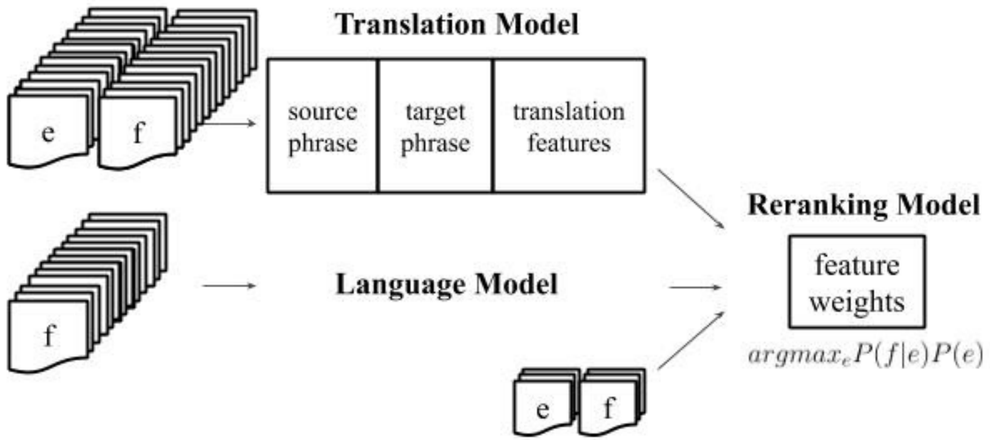

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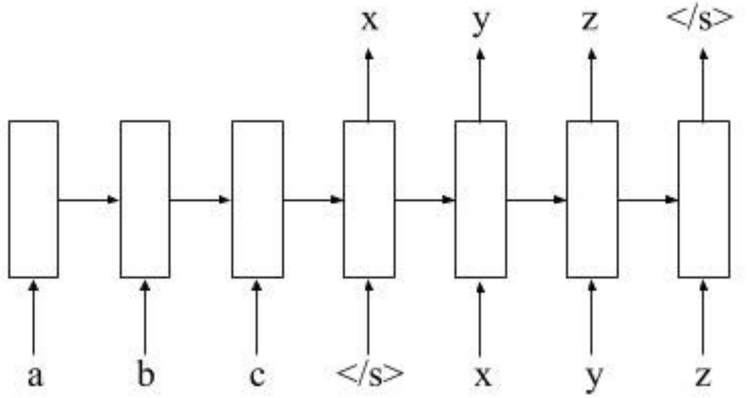

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- Let's call this vector of features ***z***.
- If ***z*** is well-chosen, it will be easy to predict from ***x*** (the words), and it will make it easy to predict the label, *y*.

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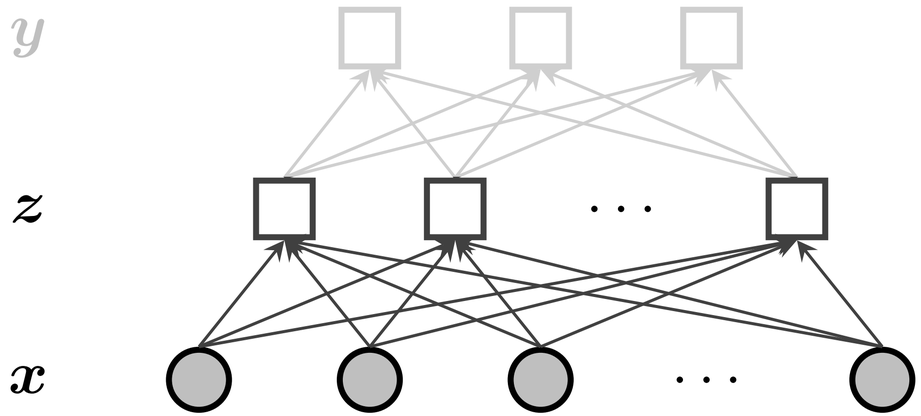

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- Let's predict each z_k from $\boldsymbol{x}$ by binary logistic regression:

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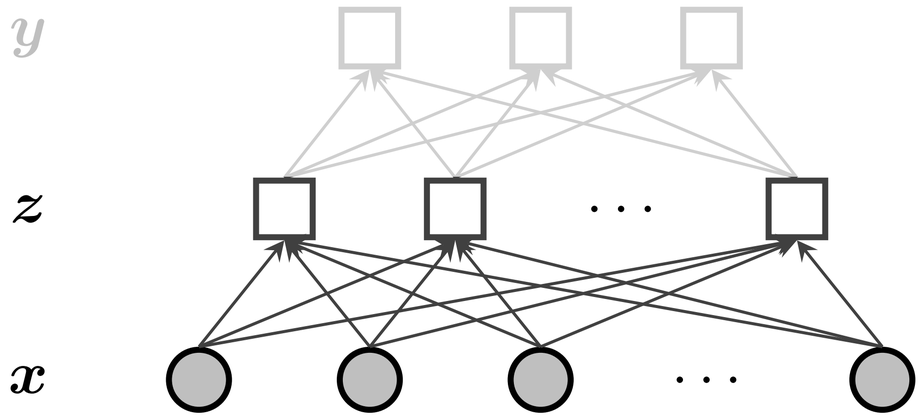

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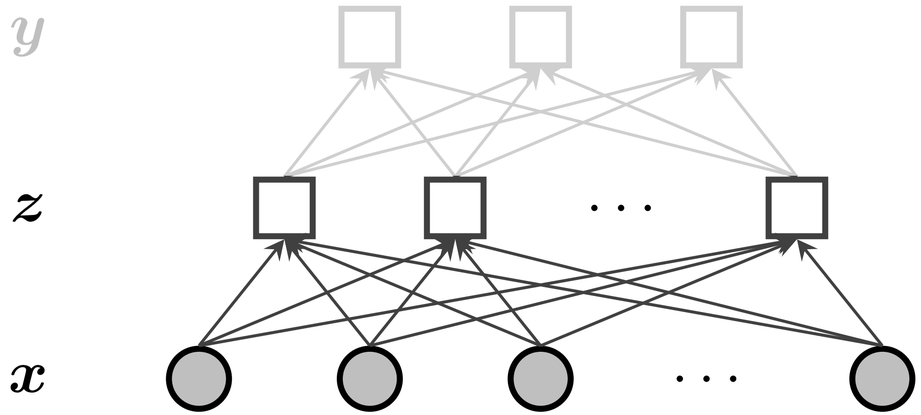

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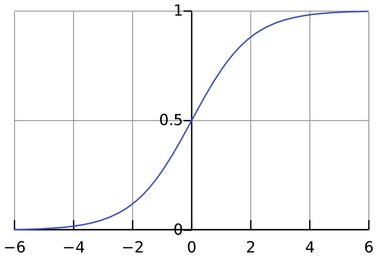

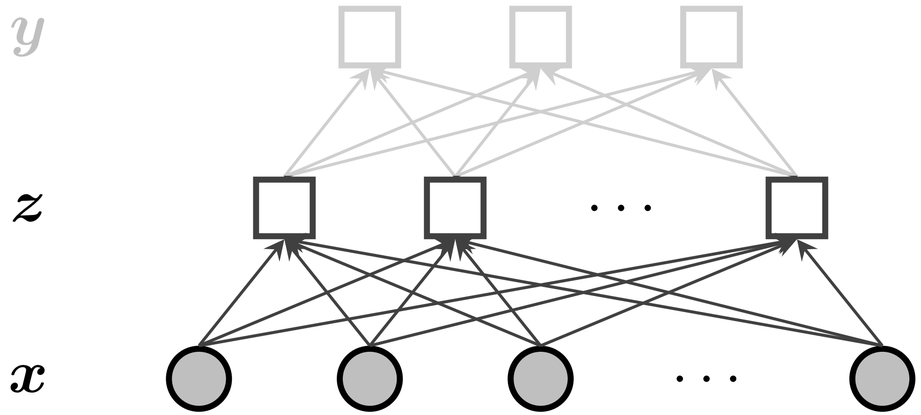

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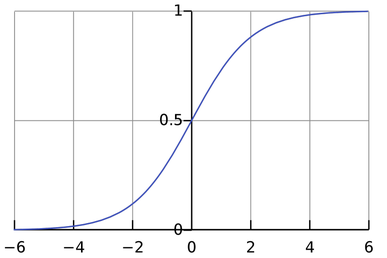

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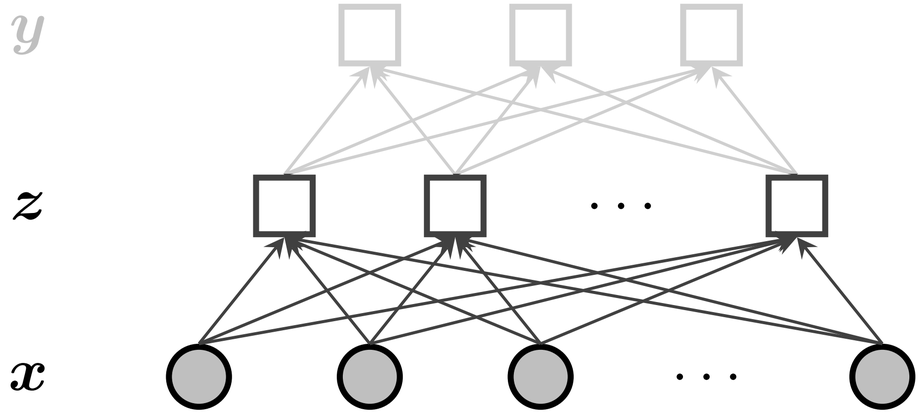

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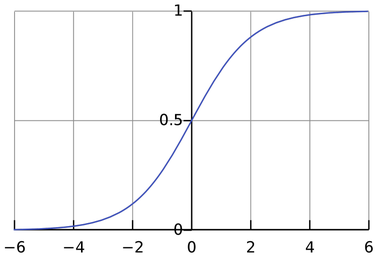

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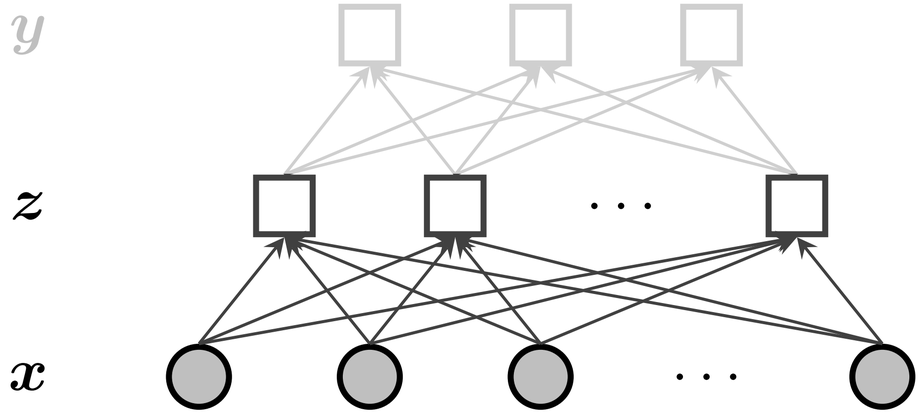

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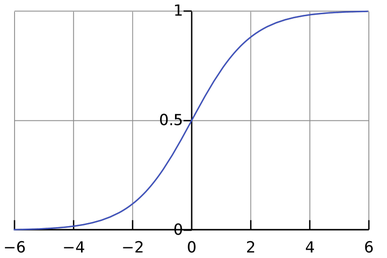

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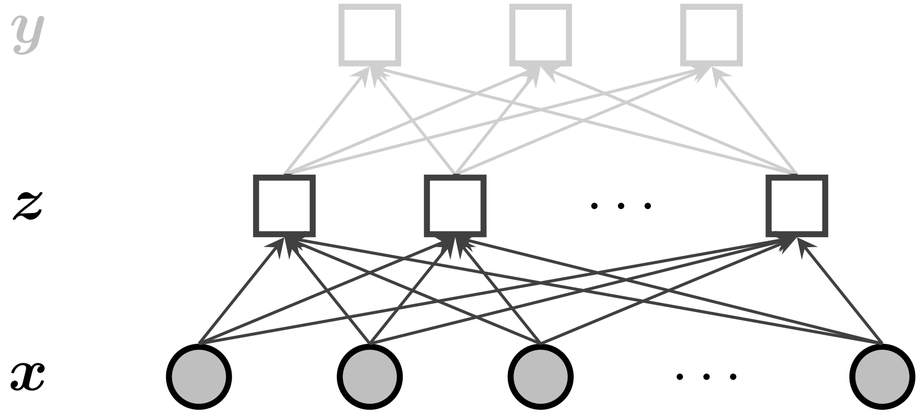

matrix-vector product. dims: [k, V] * [V, 1] = [k, 1]

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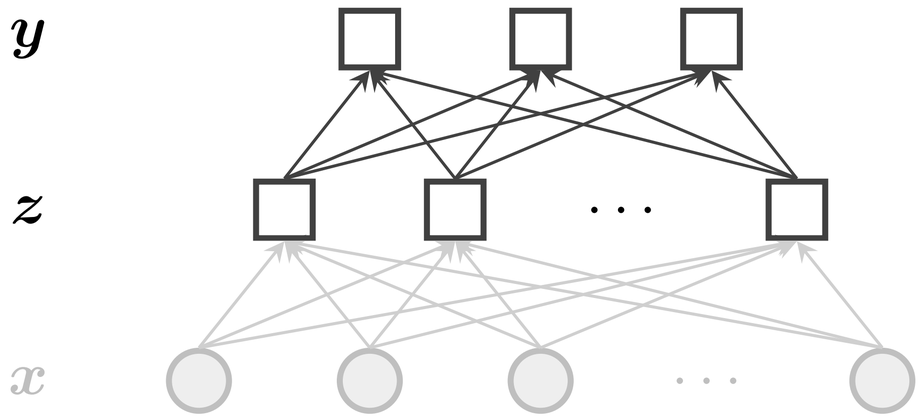

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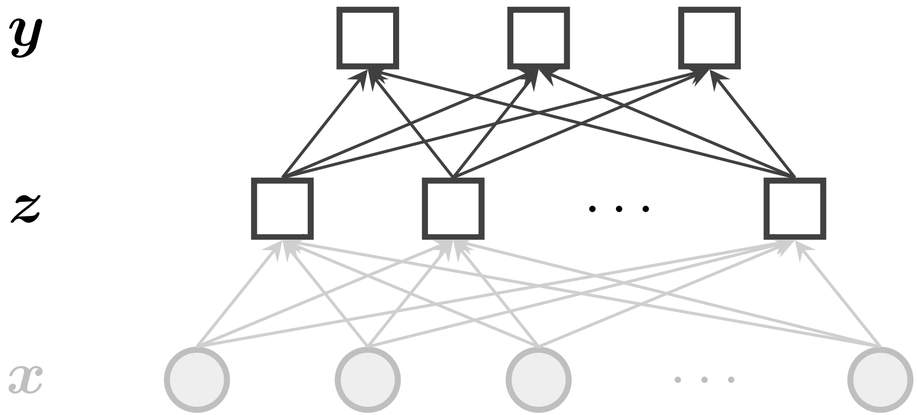
- Next we predict y from $\boldsymbol{z}$, again using logistic regression (multiclass):

$$\Pr(y = j \mid z) = \frac{\exp(\boldsymbol{\theta}_j^{(z \to y)} \cdot \boldsymbol{z} + b_j)}{\sum_{j' \in \mathcal{Y}} \exp(\boldsymbol{\theta}_{j'}^{(z \to y)} \cdot \boldsymbol{z} + b_{j'})}$$



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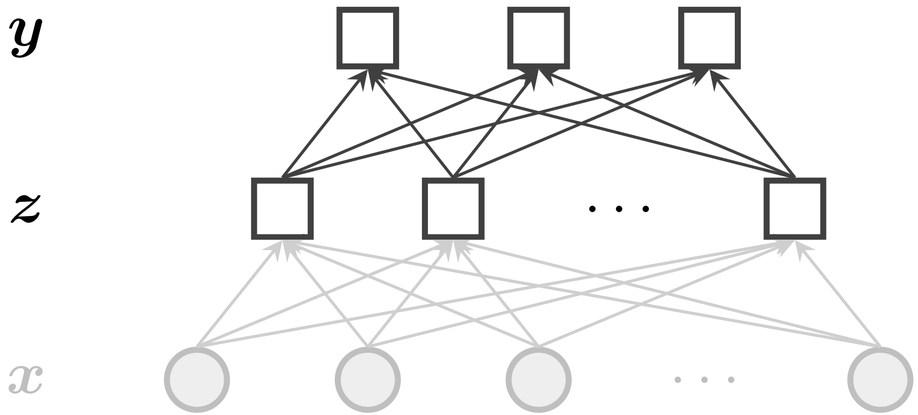

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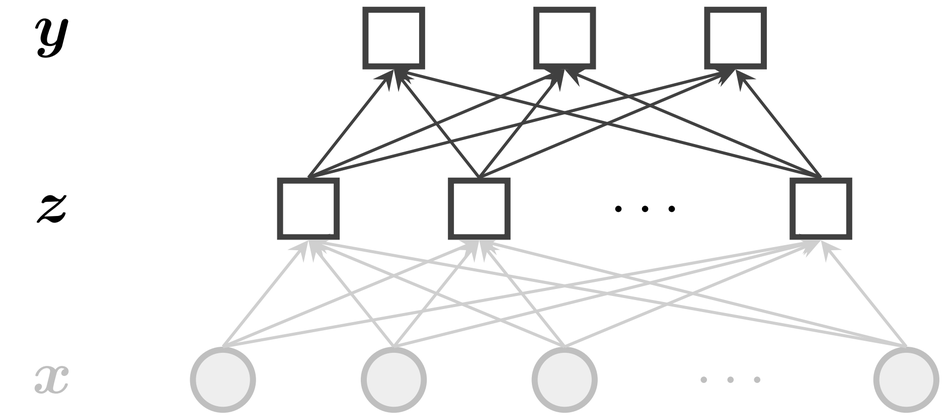
Vector of probabilities over each possible y is denoted:

$$p(\boldsymbol{y} \mid \boldsymbol{z}) = \text{SoftMax}(\boldsymbol{\Theta}^{(z \to y)} \boldsymbol{z} + \boldsymbol{b})$$



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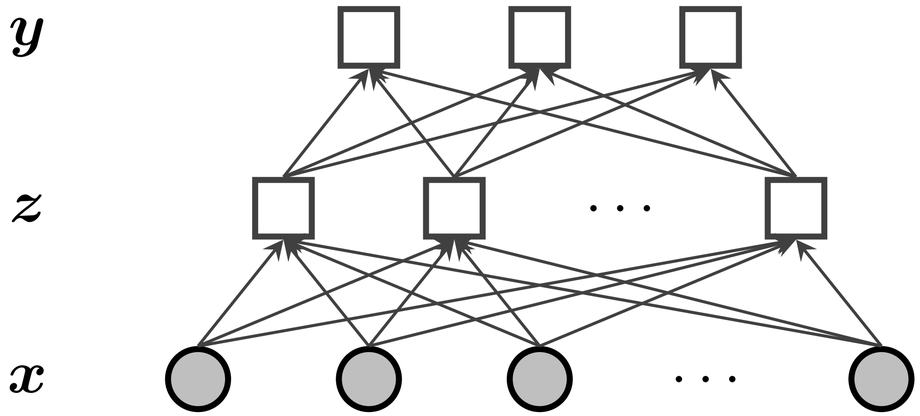

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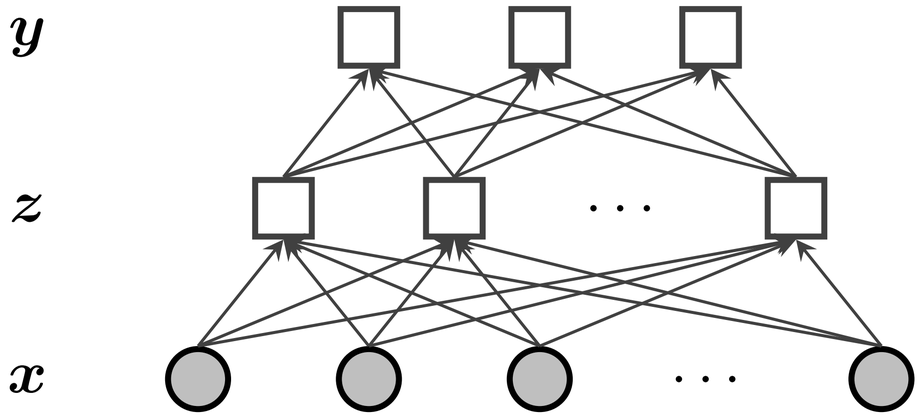

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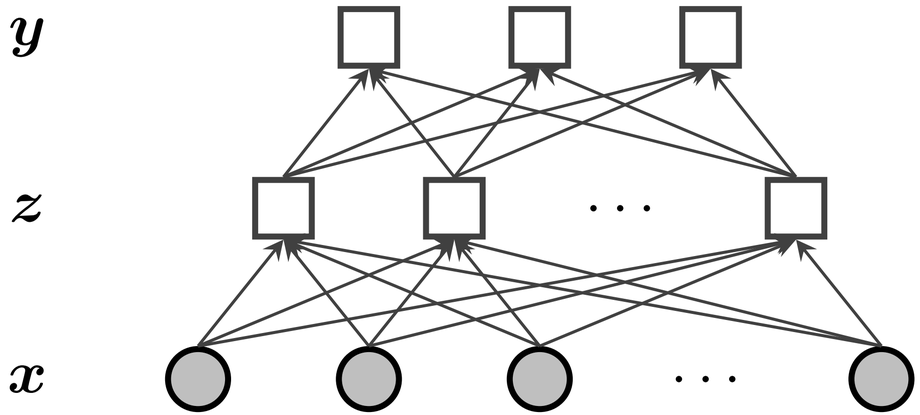

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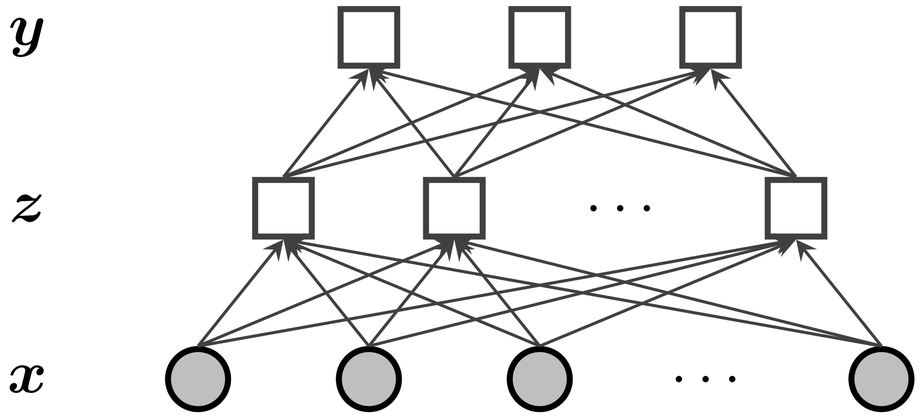

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- We can have multiple hidden layers $\boldsymbol{z}^{(1)}$, $\boldsymbol{z}^{(2)}$, … adding even more expressiveness.
- To summarize:

$$\boldsymbol{z} = \sigma(\boldsymbol{\Theta}^{(x \to z)} \boldsymbol{x})$$

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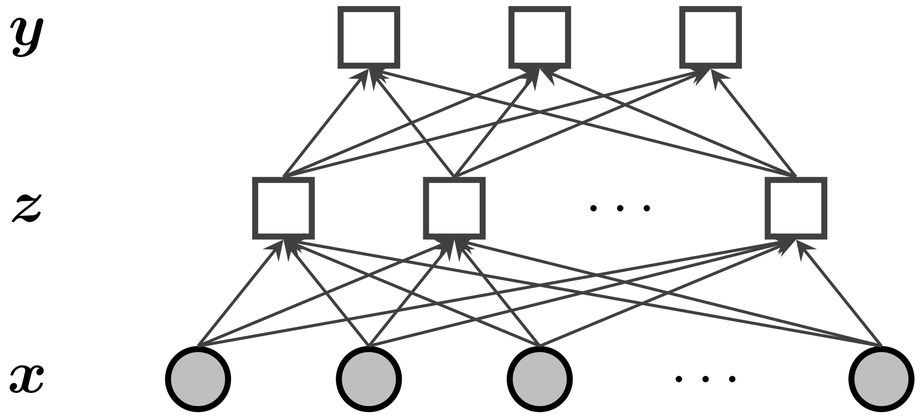
$$\sigma(\boldsymbol{\Theta}^{(x \to z)} \mathbf{x}) = \left[\sigma(\boldsymbol{\theta}_1^{(x \to z)} \cdot \mathbf{x}), \sigma(\boldsymbol{\theta}_2^{(x \to z)} \cdot \mathbf{x}), ..., \sigma(\boldsymbol{\theta}_{K_z}^{(x \to z)} \cdot \mathbf{x})\right]^T$$



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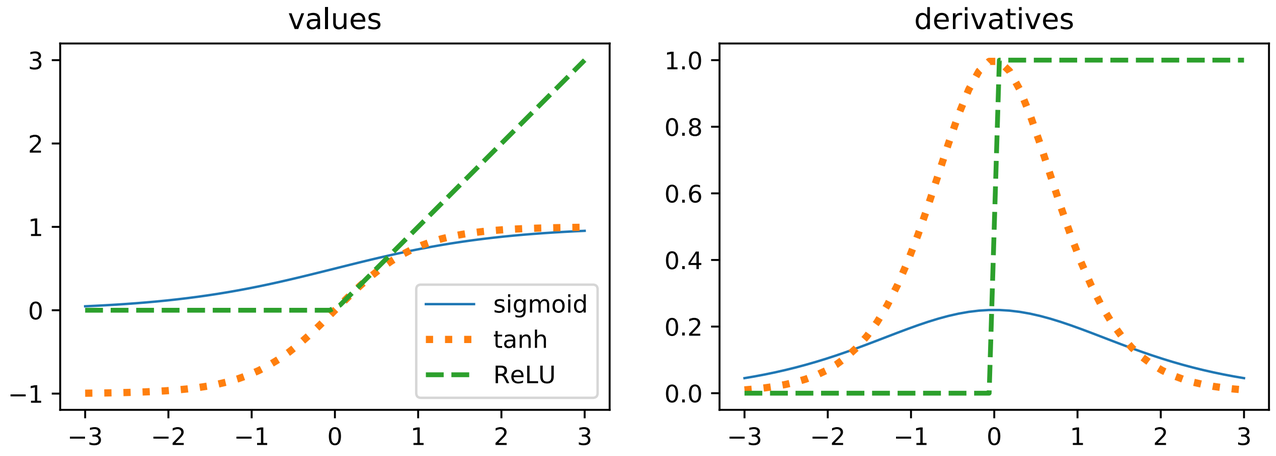

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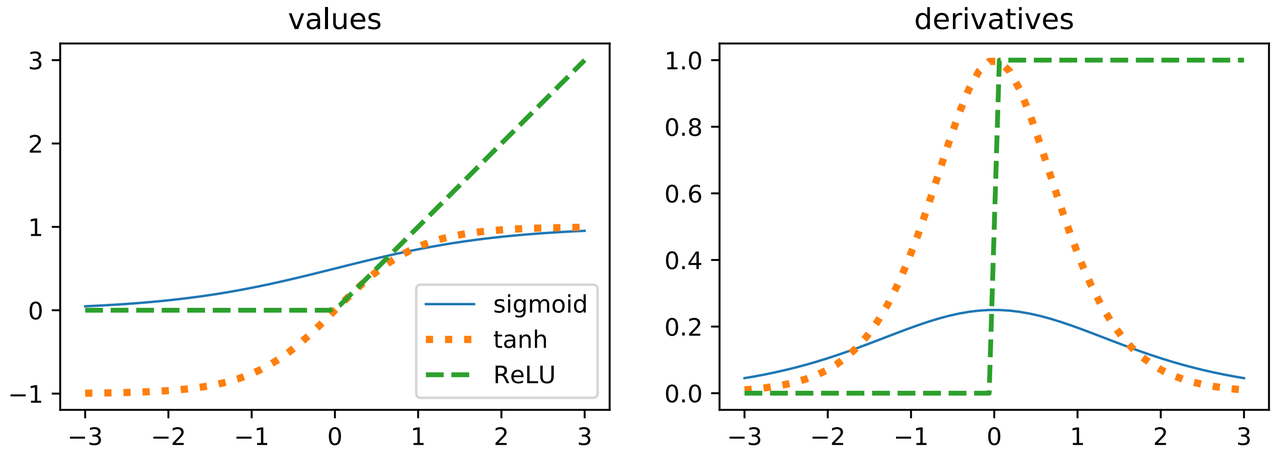

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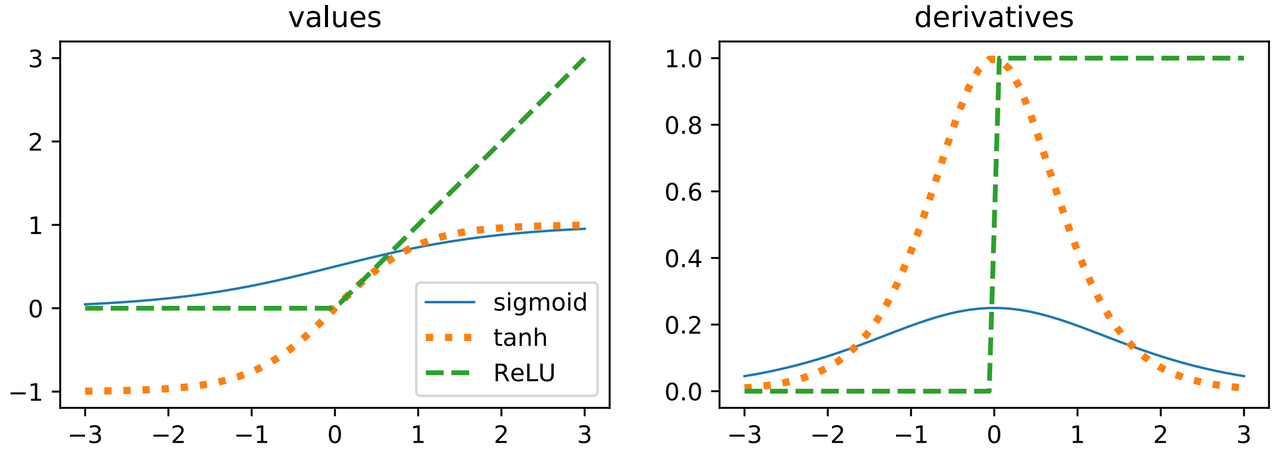

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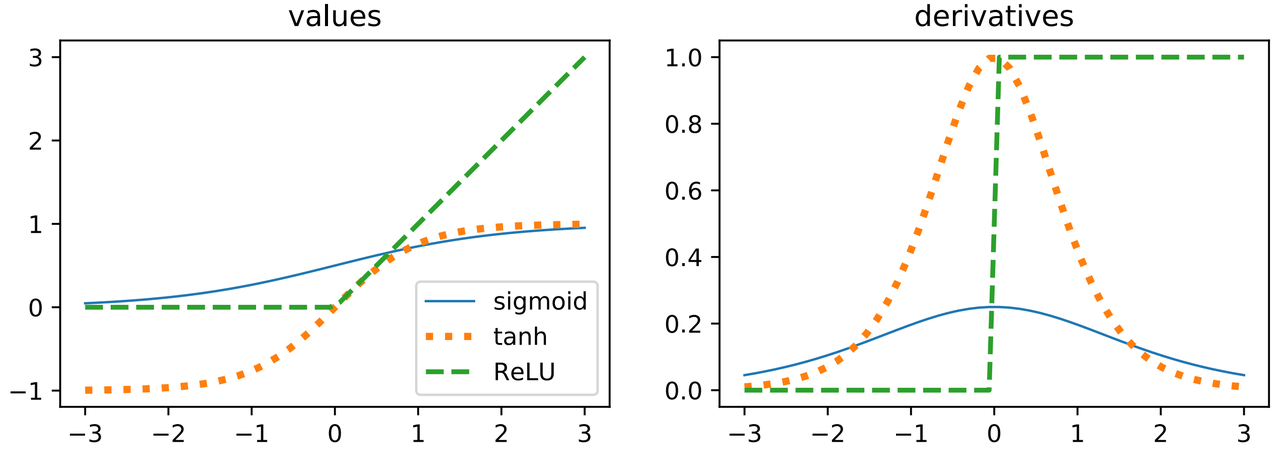
  - **Leaky ReLU**:

$$= \begin{cases} a, & a \geq 0 \\ .0001a, & \text{otherwise} \end{cases}$$



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$$\nabla_{\boldsymbol{\theta}_k^{(z \to y)}} \ell^{(i)} = \left[\frac{\partial \ell^{(i)}}{\partial \theta_{k,1}^{(z \to y)}}, \frac{\partial \ell^{(i)}}{\partial \theta_{k,2}^{(z \to y)}}, \ldots, \frac{\partial \ell^{(i)}}{\partial \theta_{k,K_y}^{(z \to y)}} \right]$$

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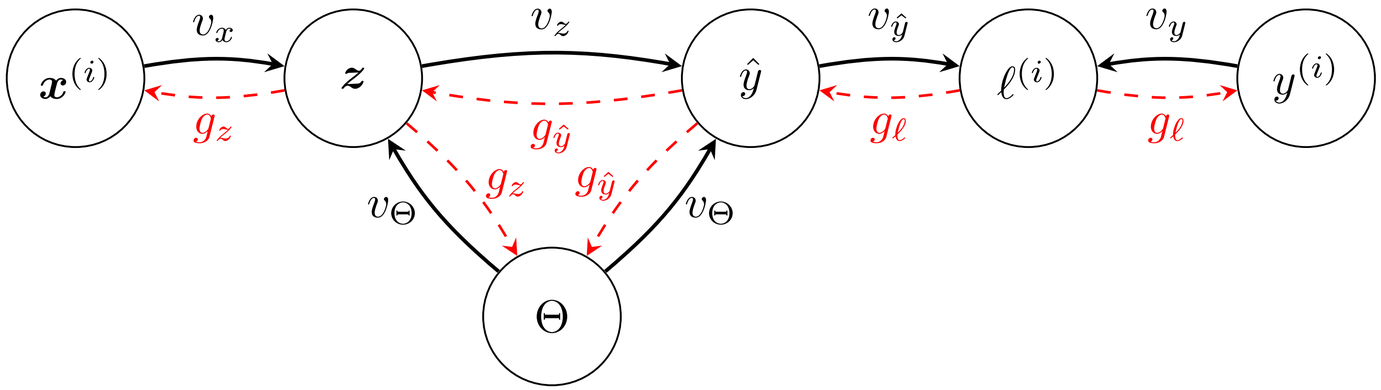

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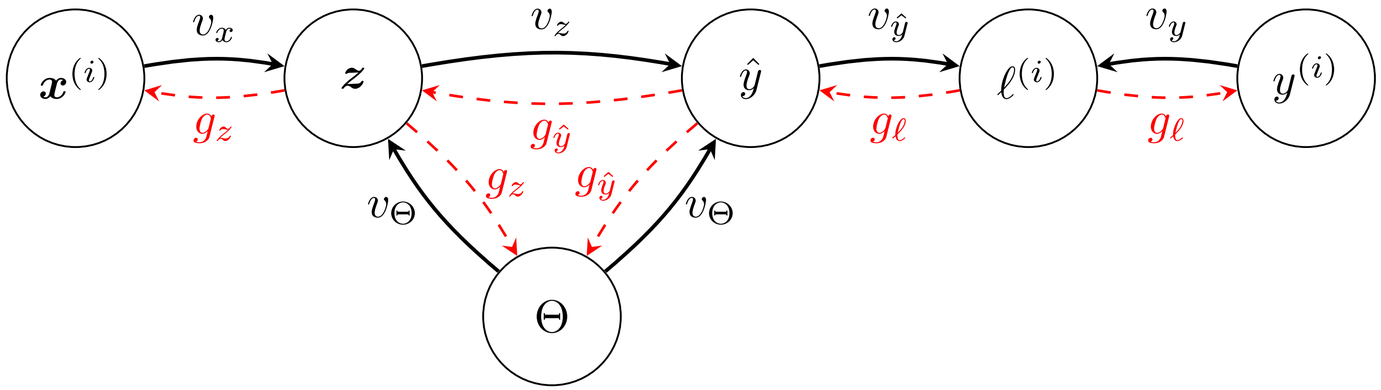

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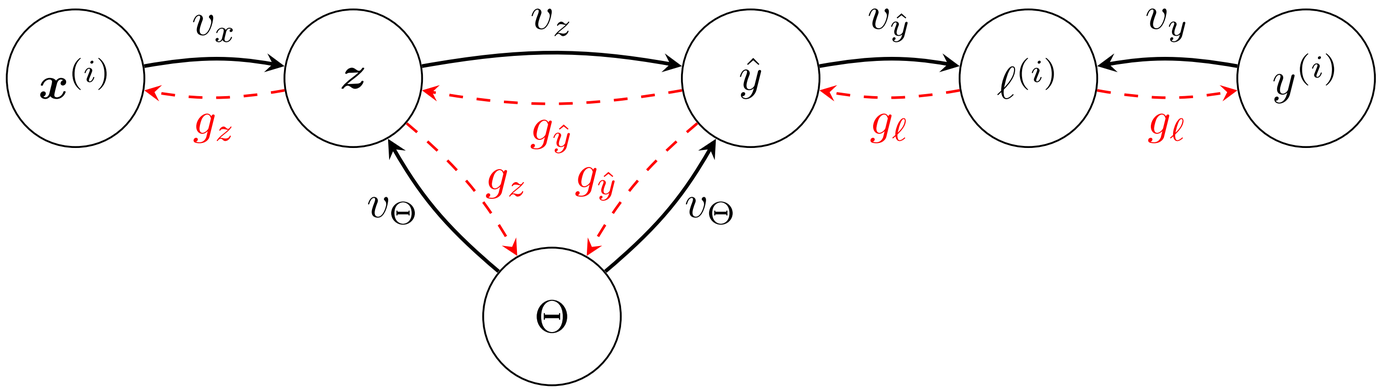

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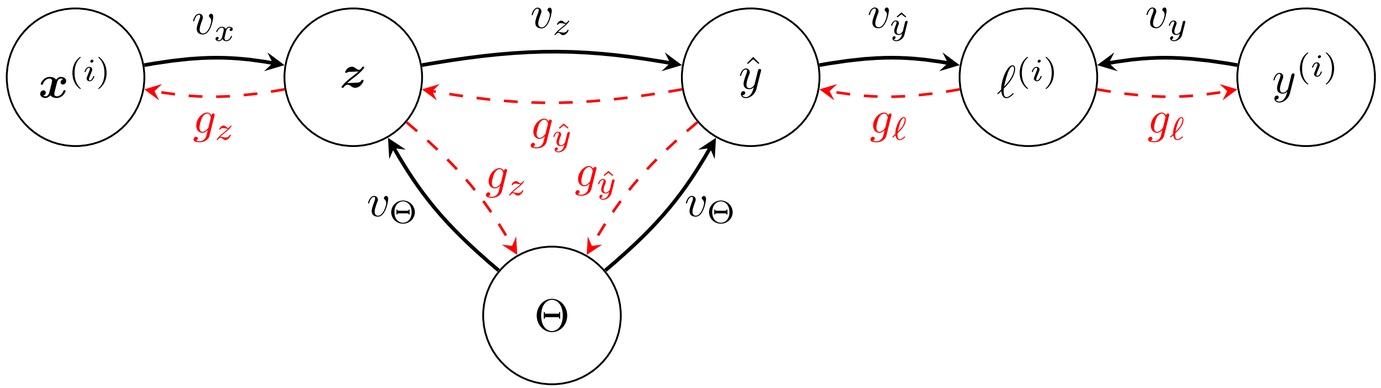
  - As long as the gradient is implemented for a layer/operation, you can add it to the graph, and let **automatic differentiation** compute updates for every layer.



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- Context is lost when this sequence is converted to a bag-of-words.
- Instead, a **lookup layer** can compute **embeddings** (real-valued vectors) for each type, resulting in a matrix $\mathbf{X}^{(0)} \in \mathbb{R}^{K_e \times M}$

$\boldsymbol{w}$ =

-1.36	1.77	0.71	-0.25	0.11	-1.36	0.03	0.71	-0.45
-0.23	-0.58	1.43	-1.27	-0.71	-0.23	0.69	1.43	1.88
0.84	-0.33	0.11	1.36	-1.08	0.84	0.14	0.11	-0.18
…	…	…	…	…	…	…	…	…
-0.067	0.93	-5.6	0.74	-0.07	-0.067	-0.36	-5.6	-1.58
the	drinks	were	strong	but	the	tacos	were	bland

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- Even if you follow all these rules, you will probably still over-estimate your classifier's performance, because real future data will differ from your test set in ways that you cannot anticipate.

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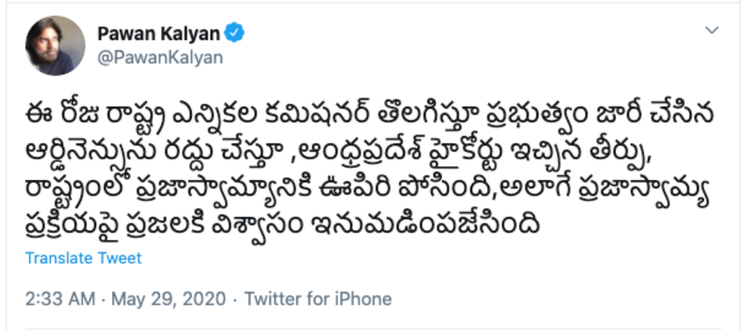

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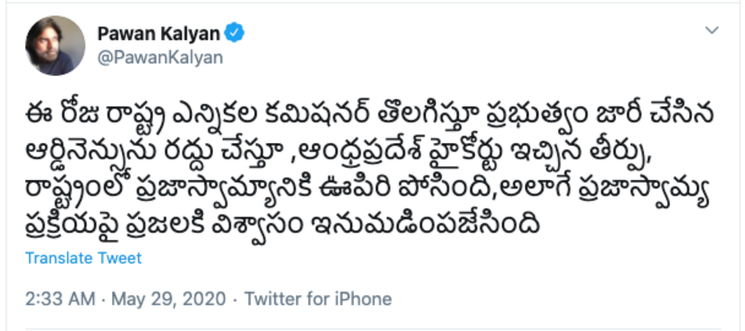

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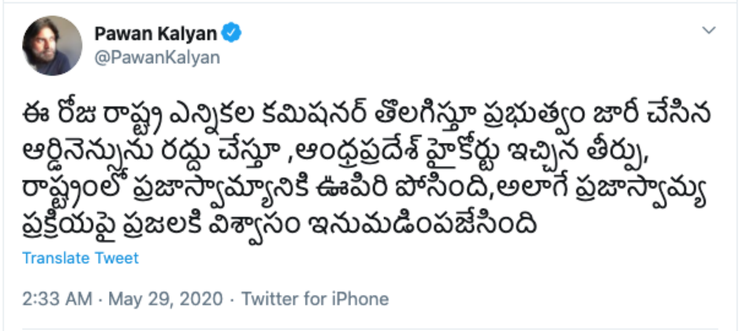

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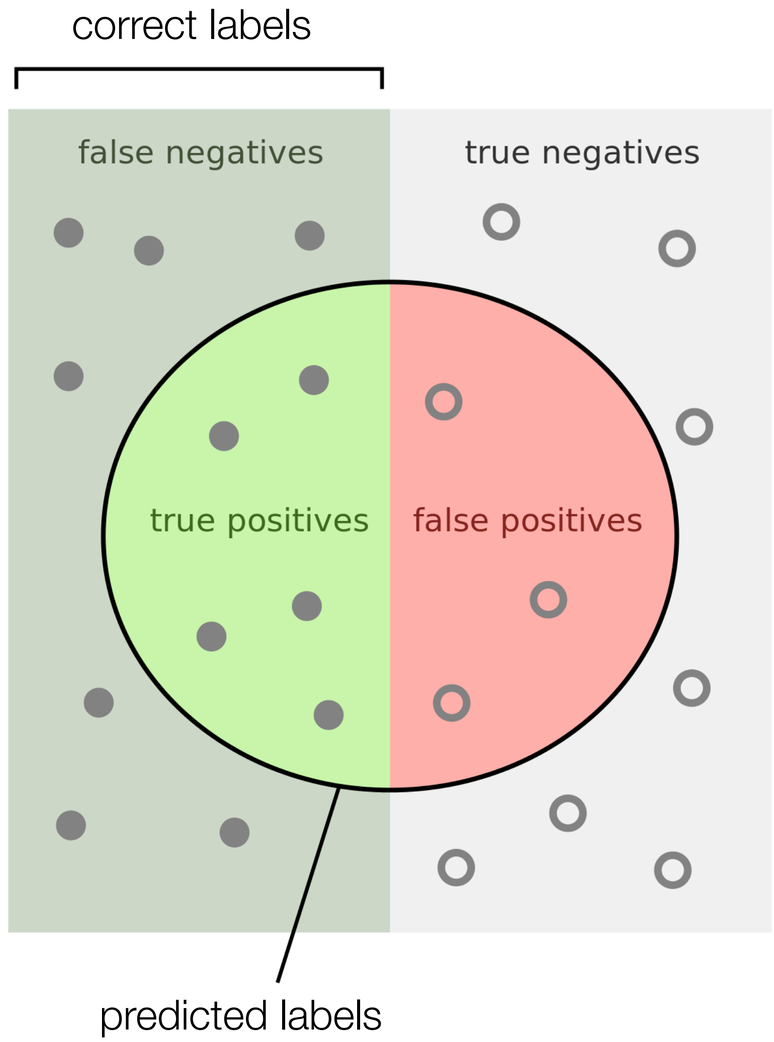
Beyond “right” and “wrong”



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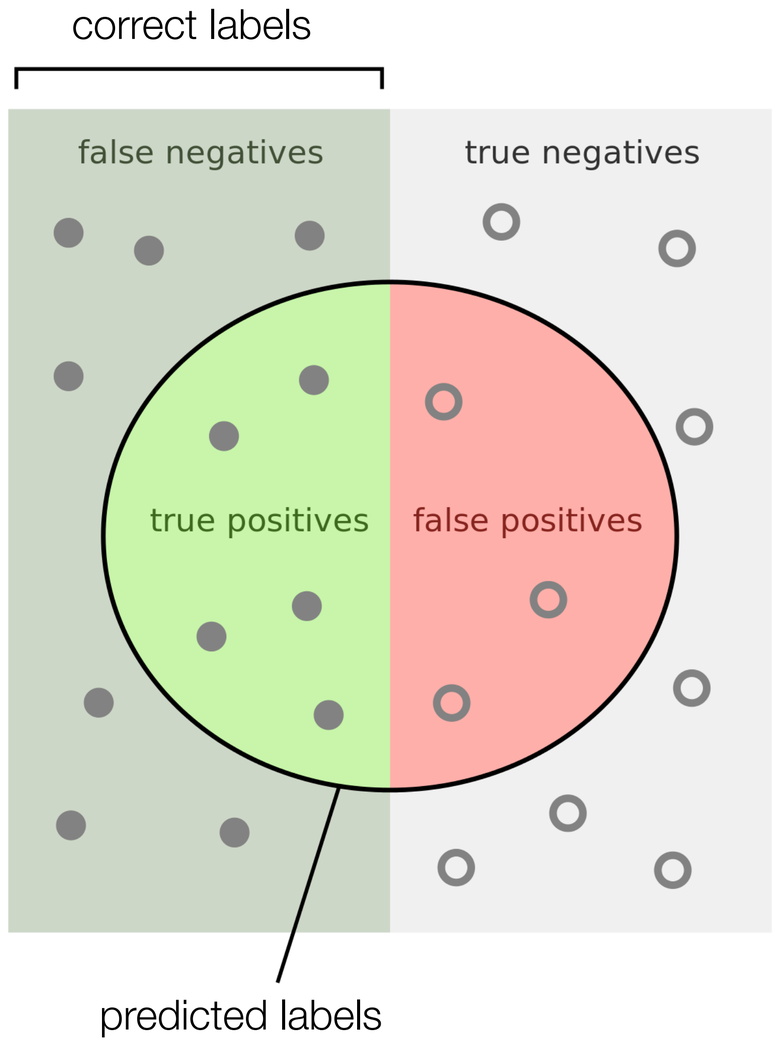

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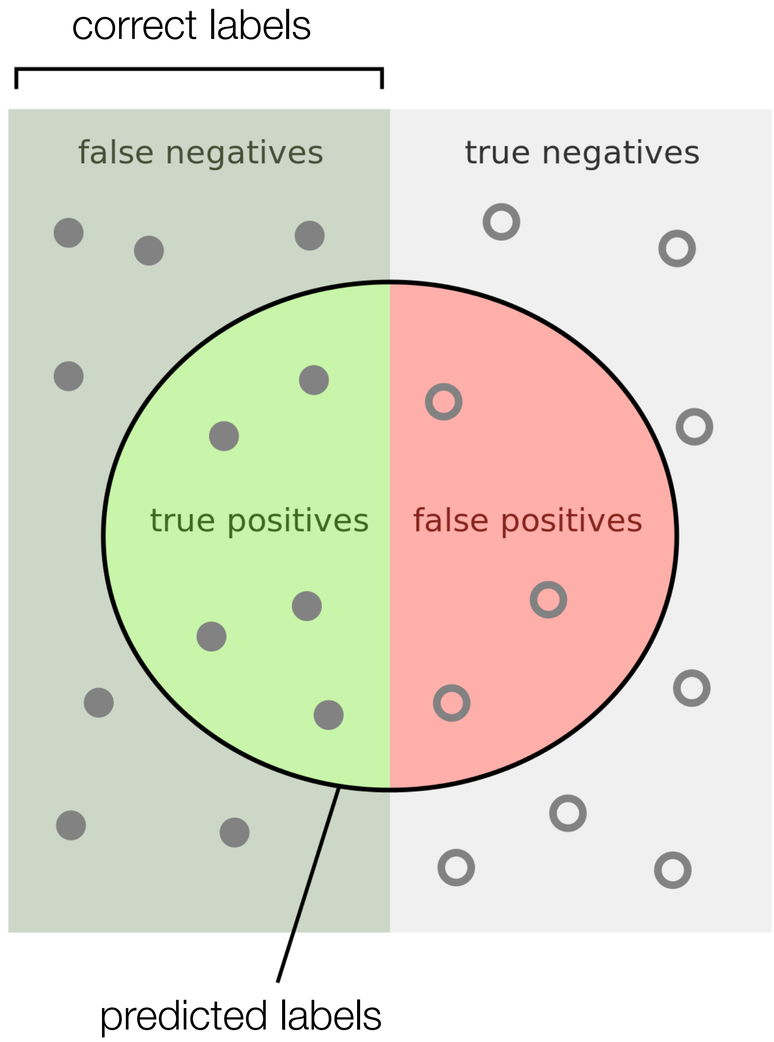

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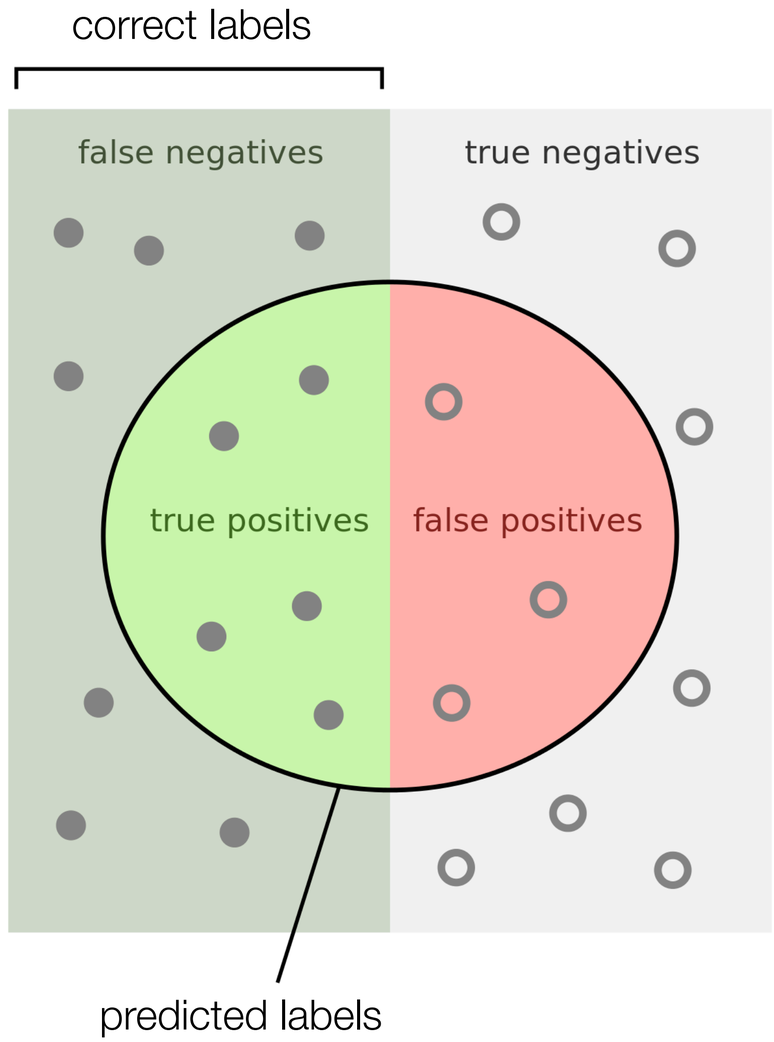

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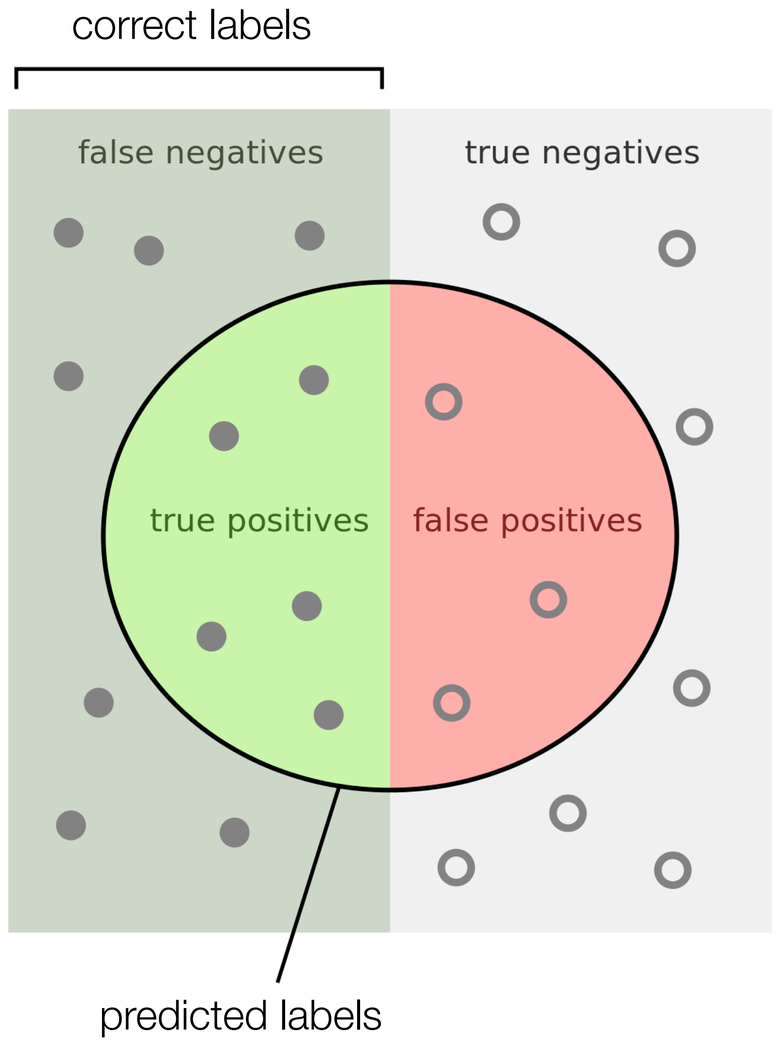

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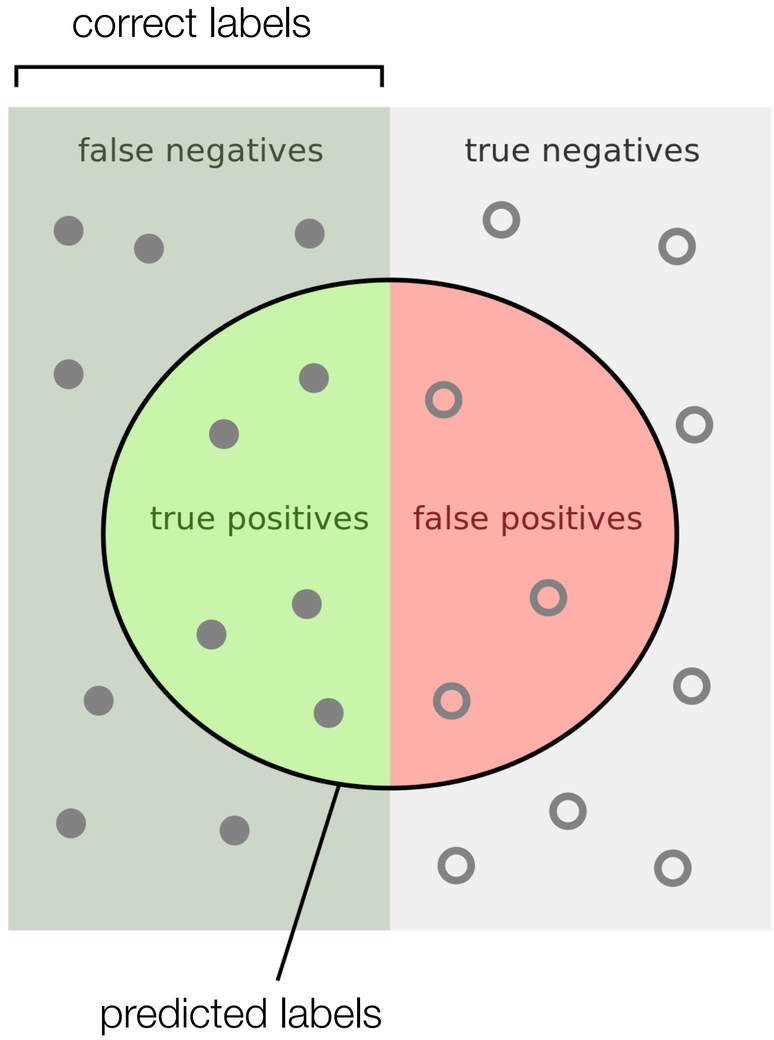

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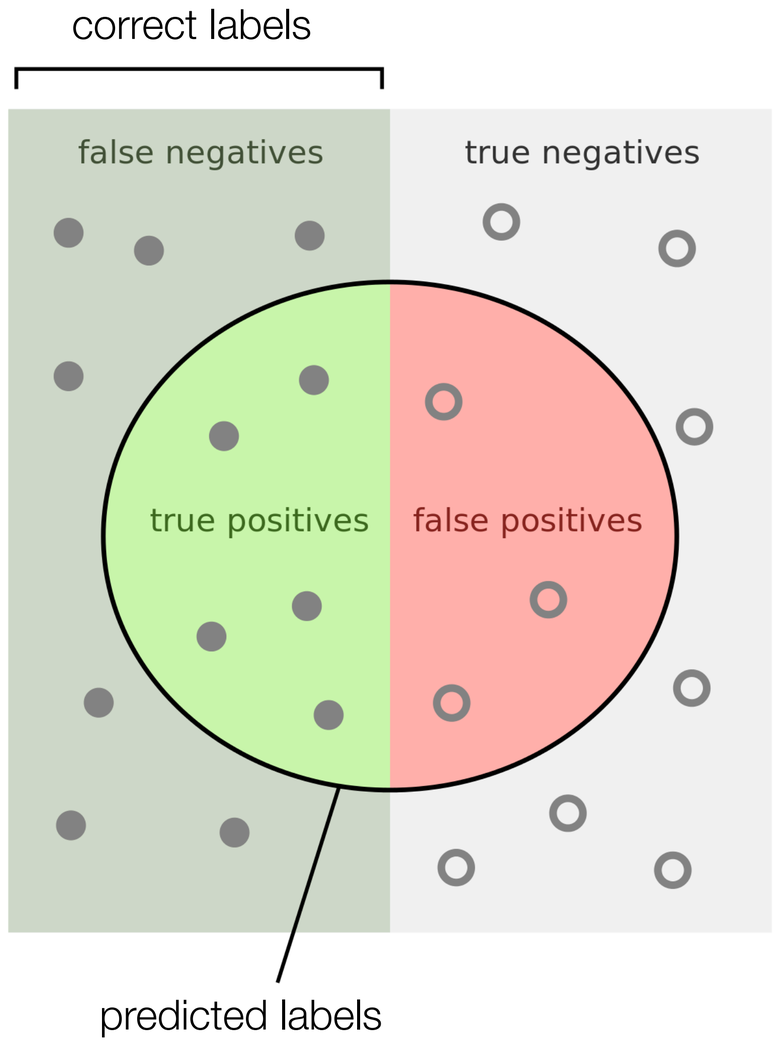
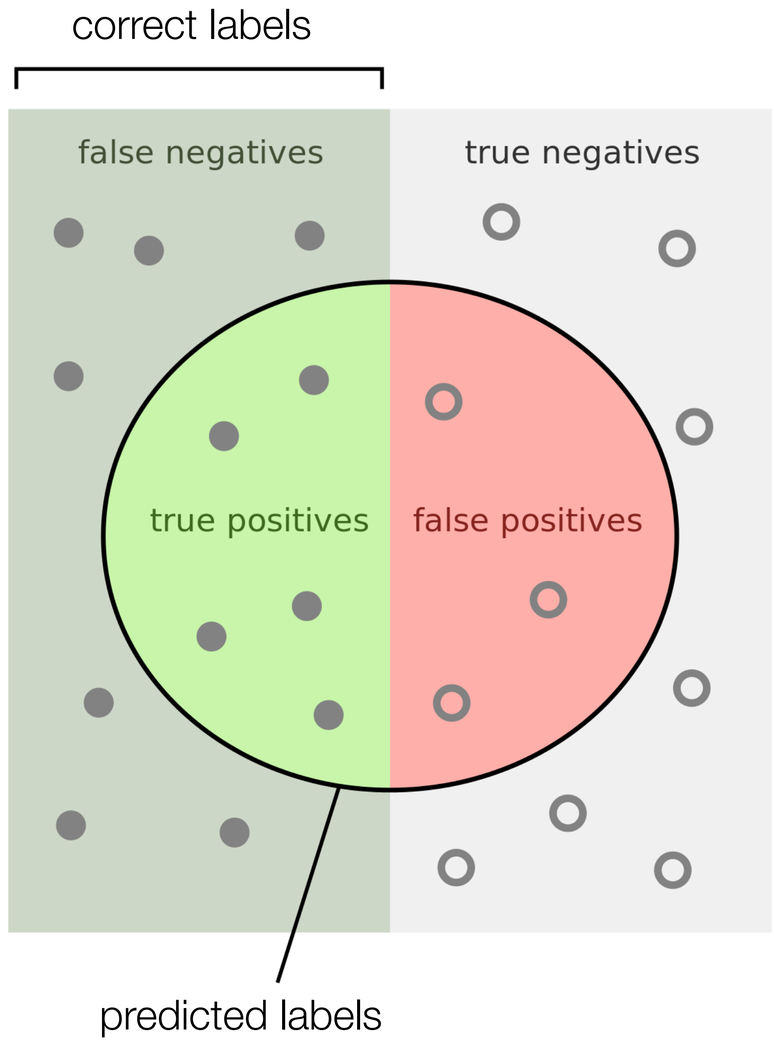


Precision and recall



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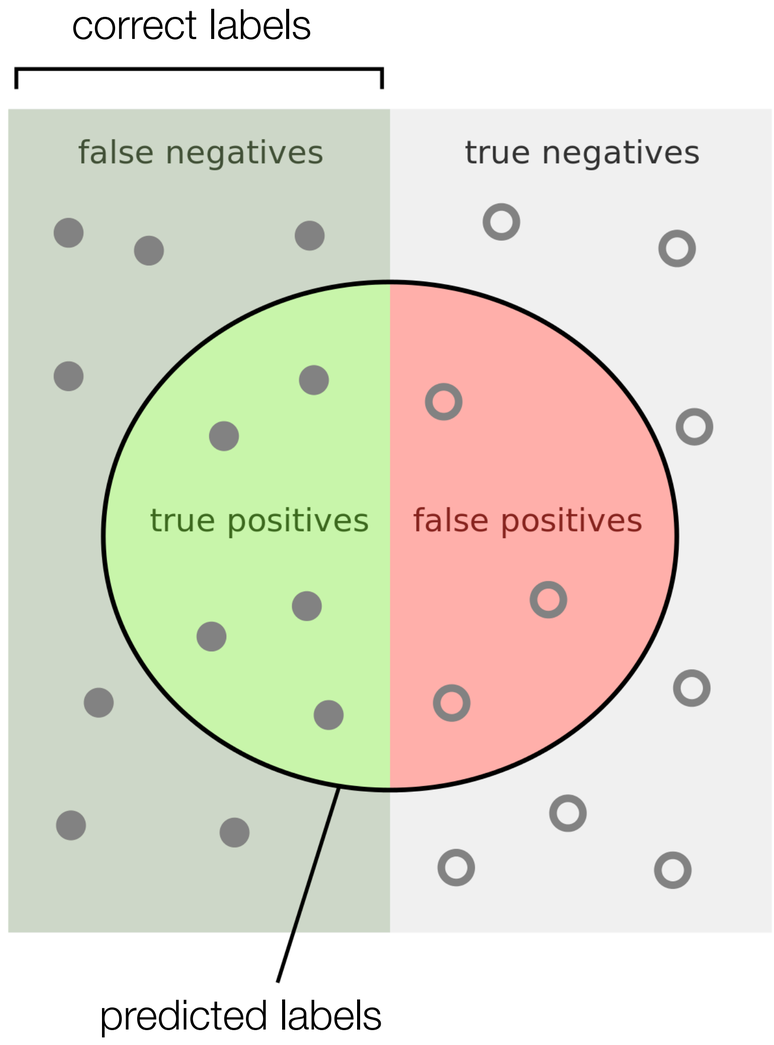

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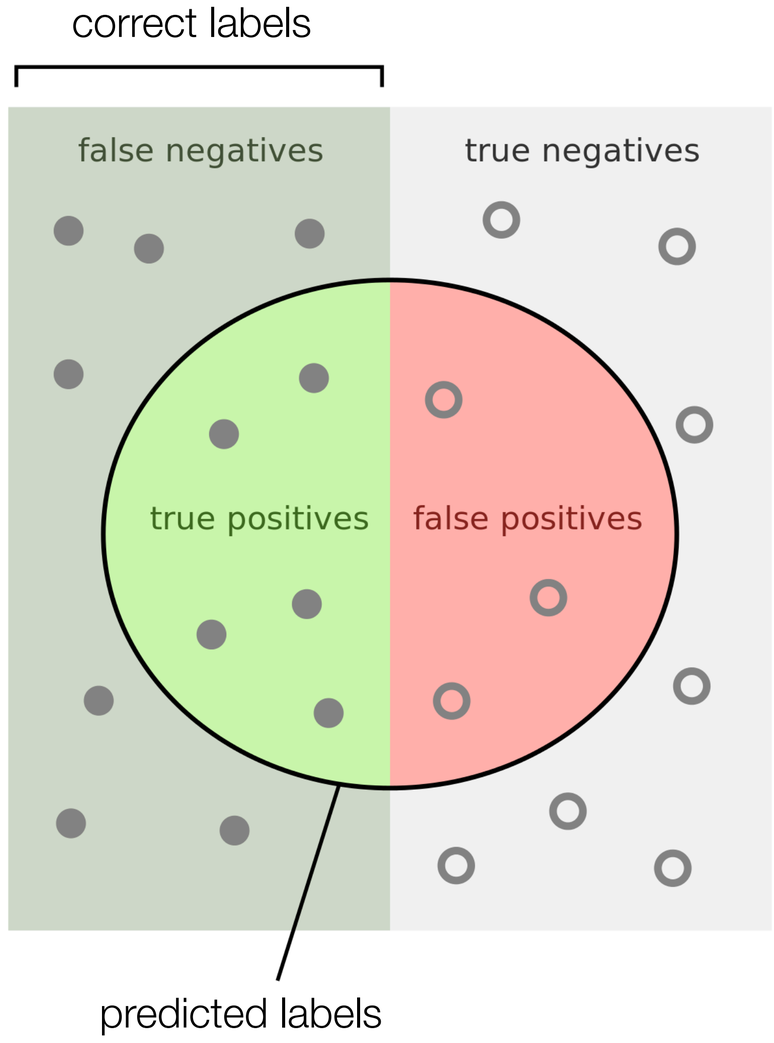

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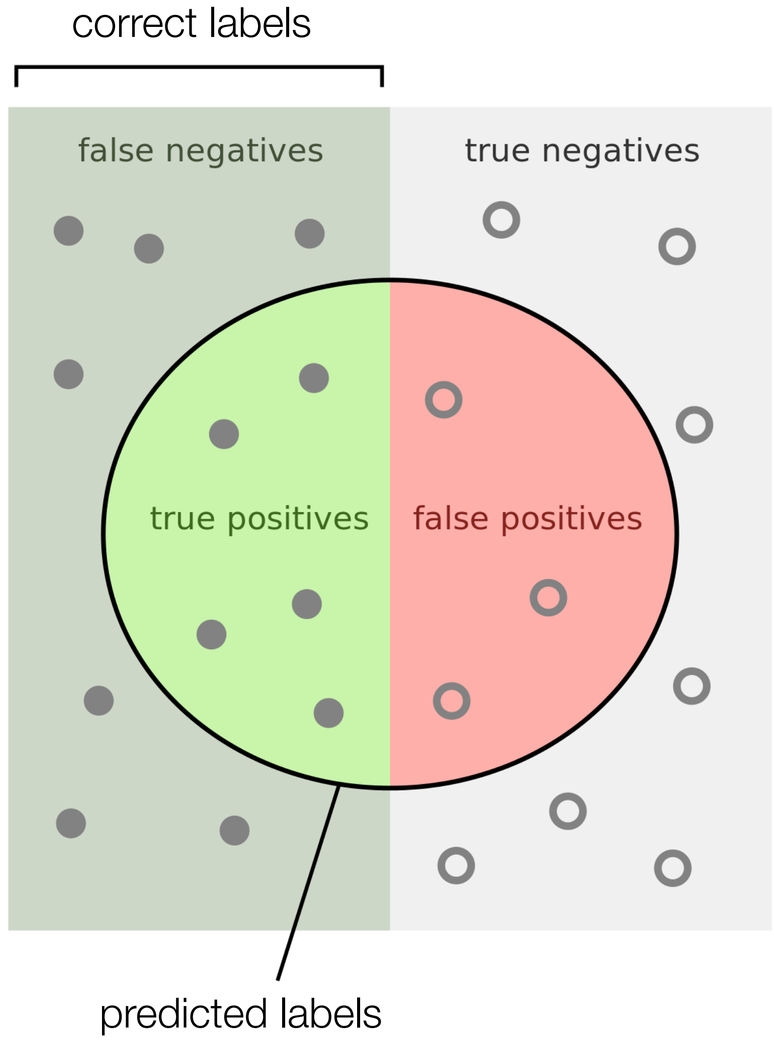

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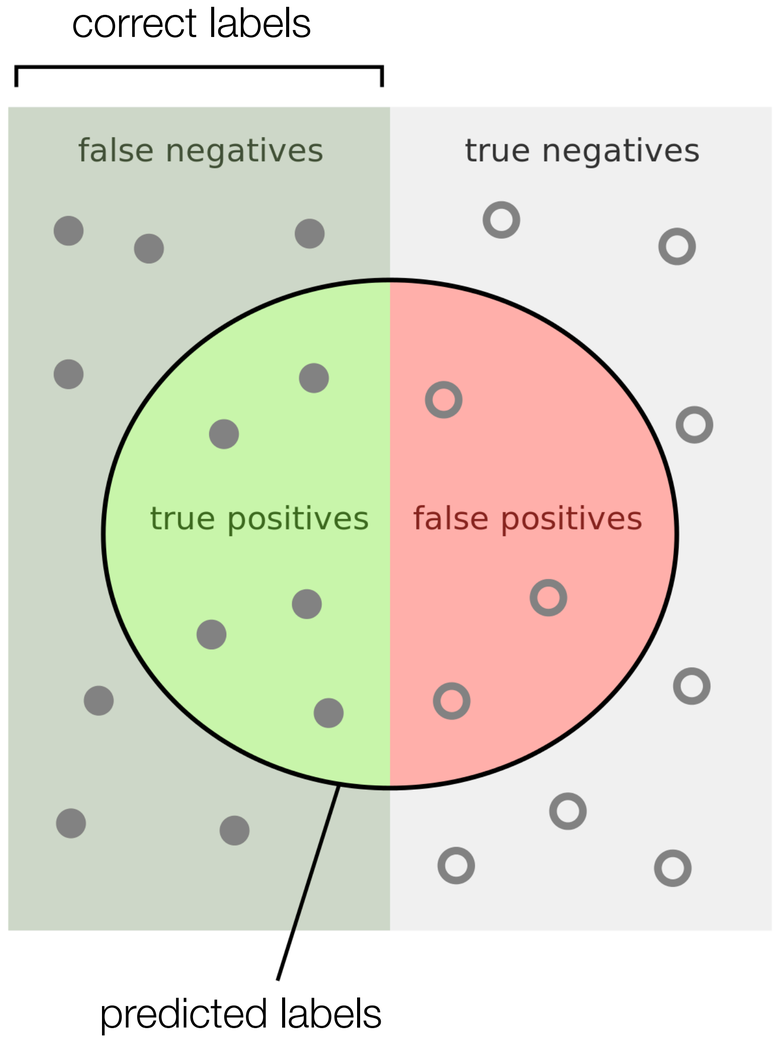

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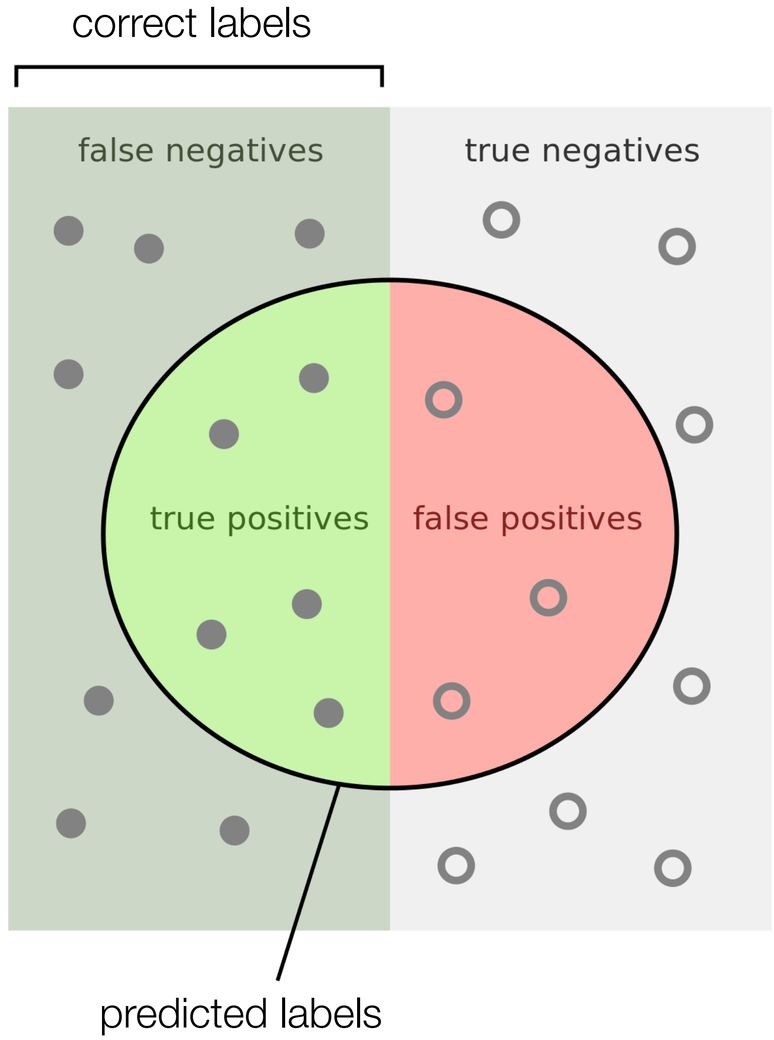

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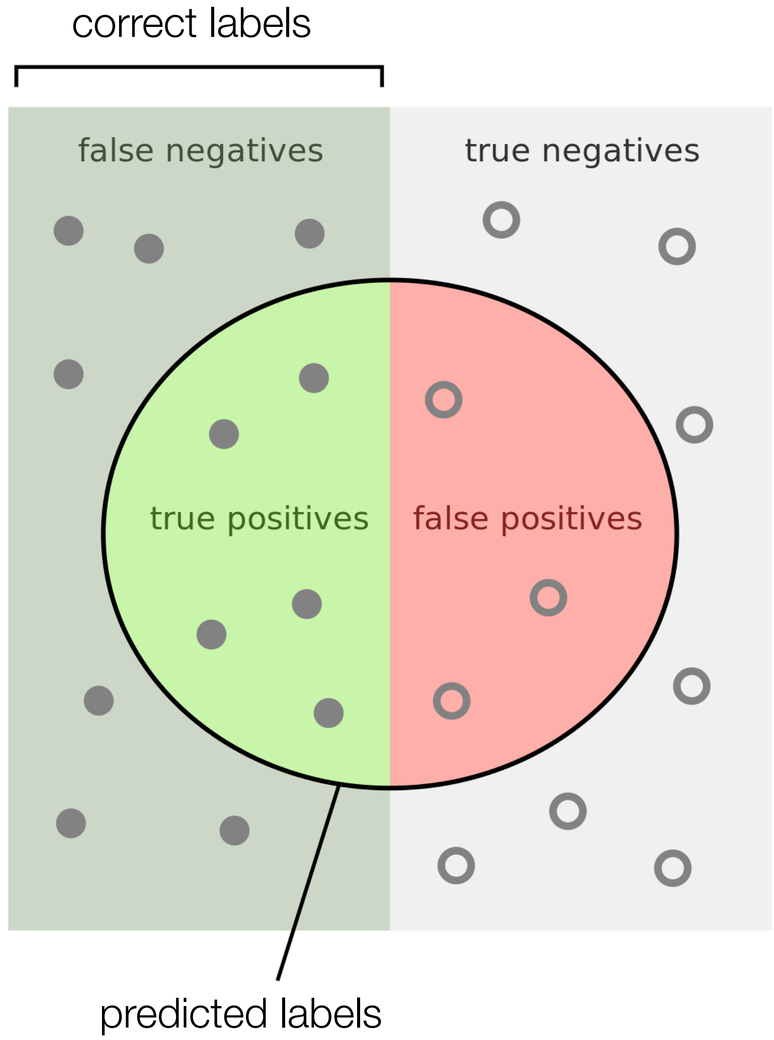

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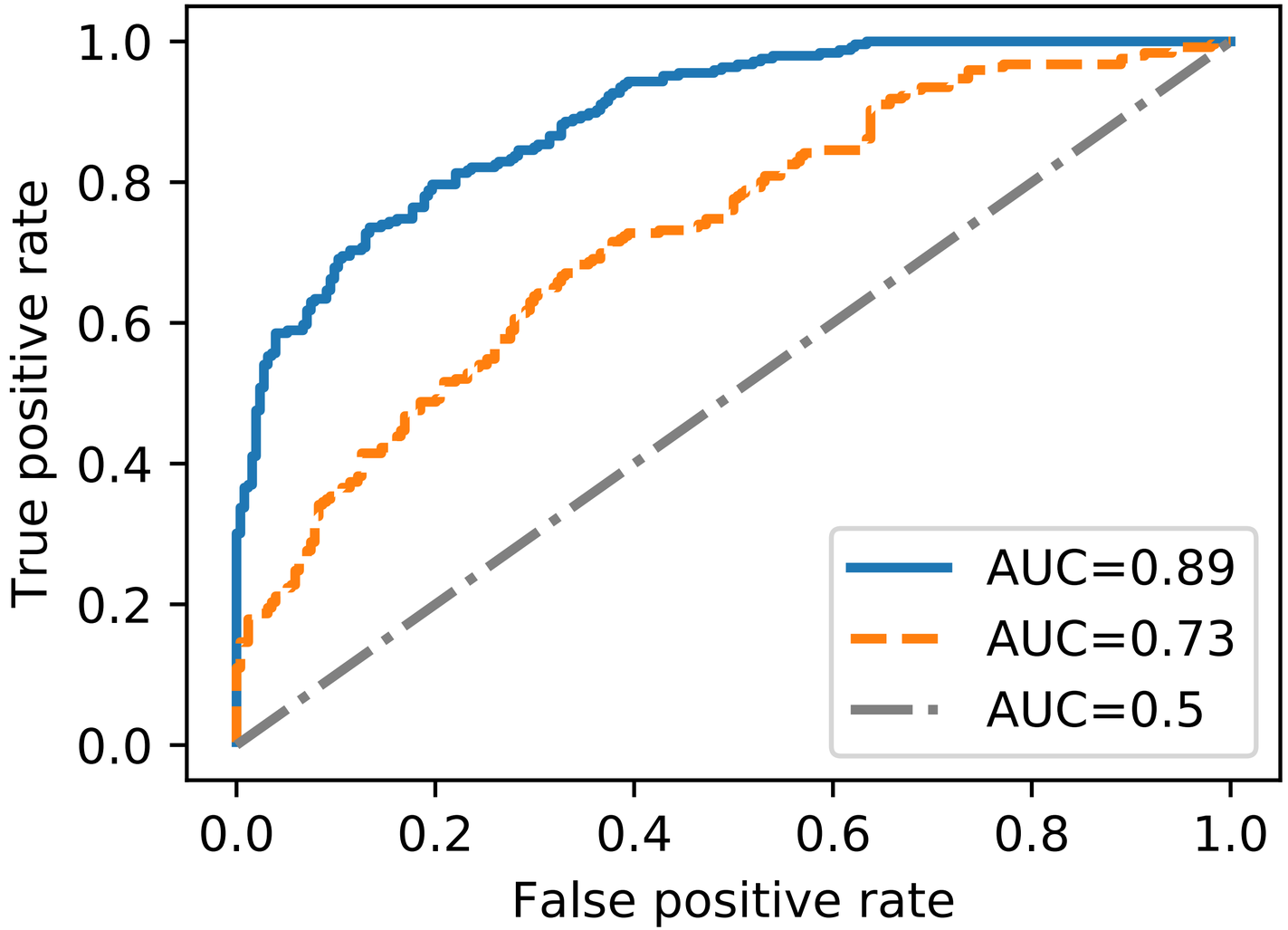
- Can generalize F-measure to adjust the tradeoff, such that recall is β-times as important as precision:

$$F_\beta = (1 + \beta^2)\frac{\mathit{precision} \cdot \mathit{recall}}{(\beta^2 \cdot \mathit{precision}) + \mathit{recall}}$$

Trading off precision and recall: ROC curve



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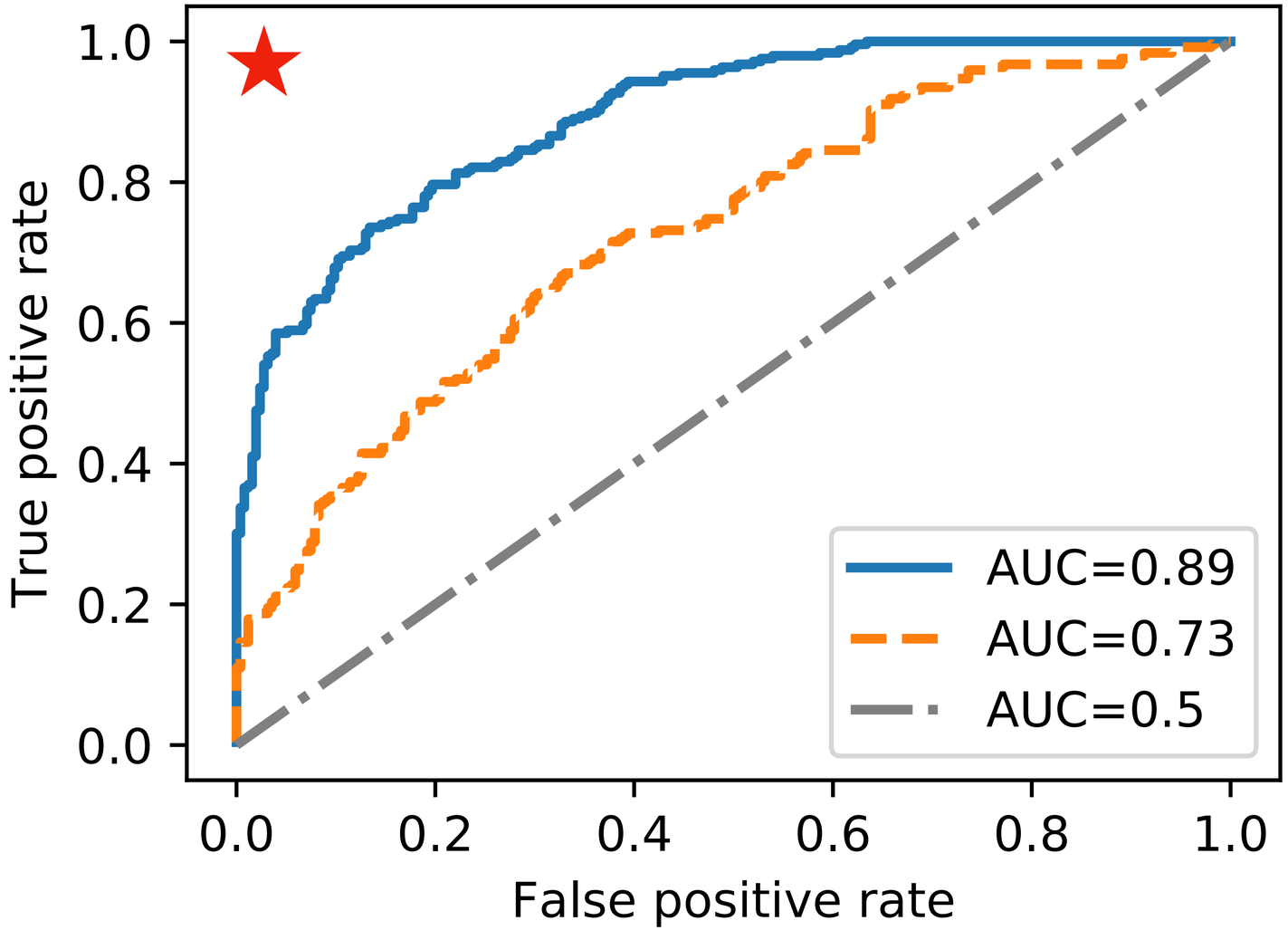

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- These probabilities are quantified by hypothesis testing.

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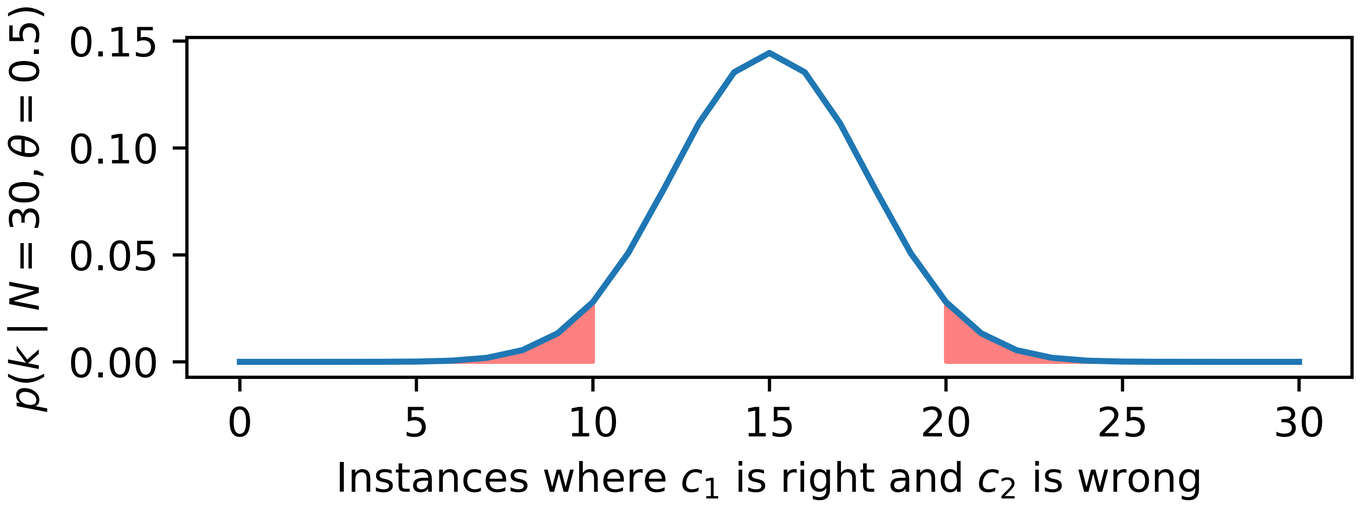

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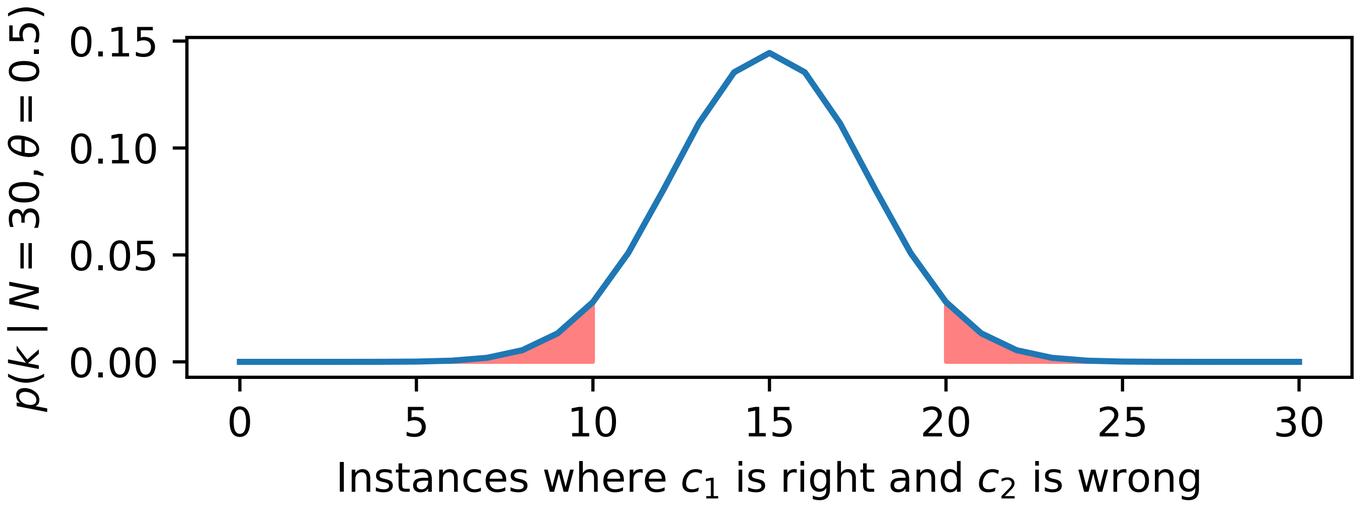

- The total probability mass in the pink region is less than 5%. If the data are in this region, we reject the null hypothesis with $p < 0.05$.

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- Hypotheses about other metrics, such as F_1, cannot be tested in this way.
- For these hypotheses, best approach is randomization: randomly sample many test sets, and count how often each hypothesis holds.

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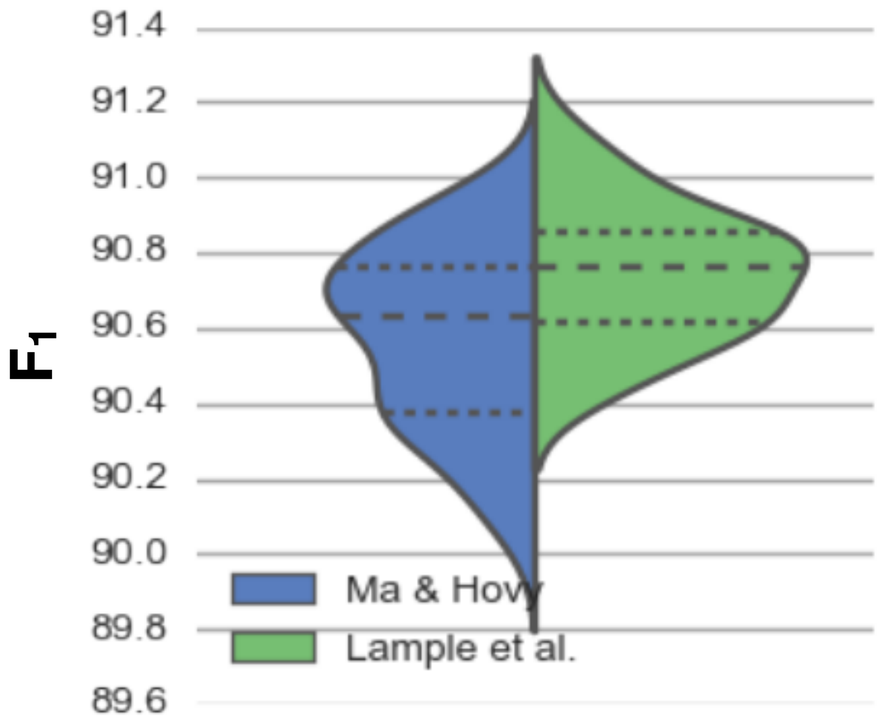

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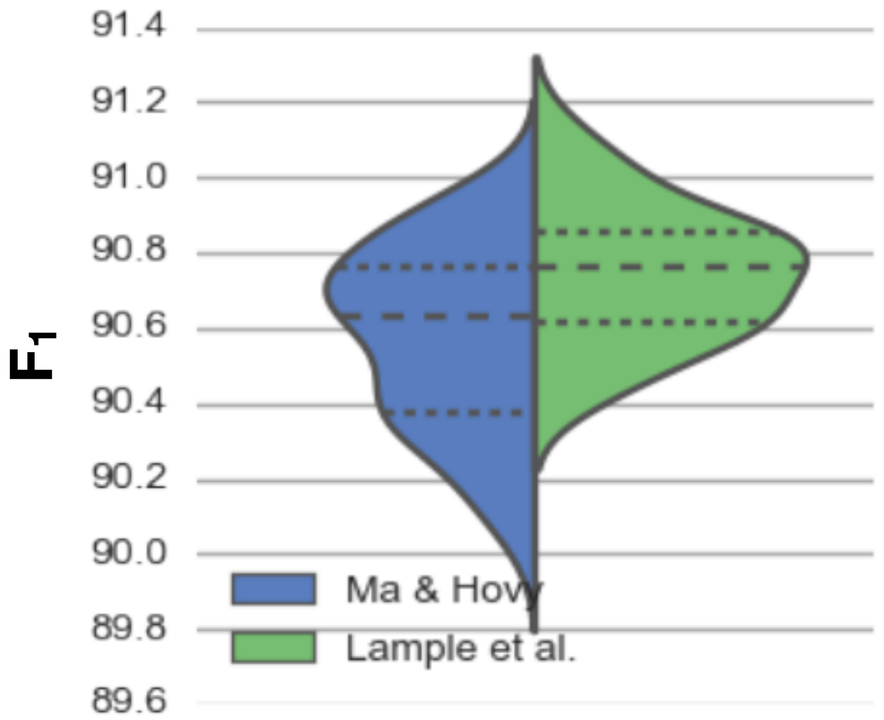
Two recent, state-of-the-art systems for NER are proposed by Ma and Hovy (2016)[5] and by Lample et al. (2016)[6]. Lample et al. report an F_1-score of 90.94% and Ma and Hovy report an F_1-score of 91.21%. Ma and Hovy draw the conclusion that their system achieves a significant improvement over the system by Lample et al.



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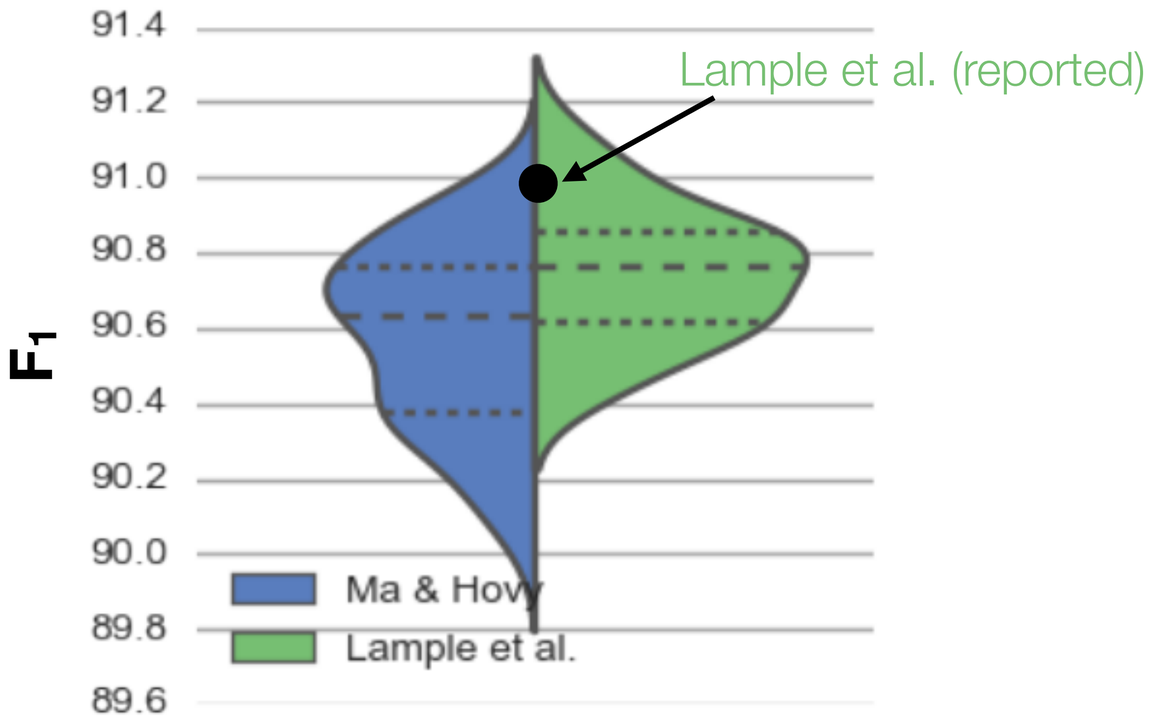

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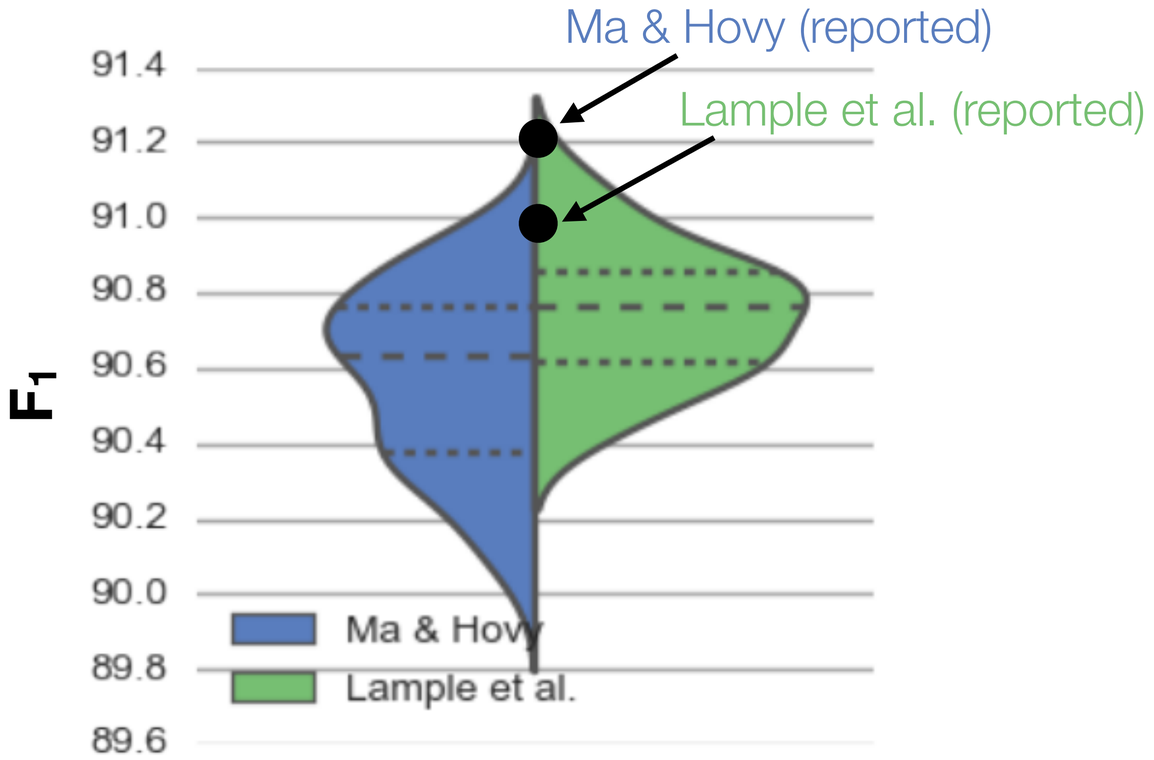

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Announcements

- **Project 1: Text classification** will be available after class today, **due Friday September 25**
- Han will lead recitation this Friday to introduce Project 1, and cover environment setup (Python, Jupyter, NumPy, PyTorch).