Feature-based Classification with the Perceptron

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(some slides borrowed from Chris Dyer)
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Feature-Based Classification

Word Sense Disambiguation (WSD)

- Given a word **in context**, predict which sense is being used.
  - Evaluated on corpora such as **SemCor**, which is fully annotated for WordNet synsets.

- For example: consider joint POS & WSD classification for ‘interest’, with 3 senses:
  - N:financial (*I repaid the loan with interest*)
  - N:nonfinancial (*I read the news with interest*)
  - V:nonfinancial (*Can I interest you in a dessert?*)

Beyond BoW

- Neighboring words are relevant to this decision.
- More generally, we can define **features** of the input that may help identify the correct class.
  - Individual words
  - Bigrams (pairs of consecutive words: *Wall Street*)
  - Capitalization (*interest* vs. *Interest* vs. *INTEREST*)
  - Metadata: document genre, author, …
- These can be used in naïve Bayes—"bag of features"
  - With overlapping features, independence assumption is *even more naïve*: $\mathrm{p}(y \mid \mathbf{x}) \propto \mathrm{p}(y) \cdots \mathrm{p}(\text{Wall} \mid y)\, \mathrm{p}(\text{Street} \mid y)\, \mathrm{p}(\text{Wall Street} \mid y)$
  - But other kinds of feature-based classifiers don't make this naïve assumption.

Feature Extraction

x = Wall Street vets raise concerns about interest rates , politics

spelling feature

	$\phi(\mathbf{x})$
bias	1
capitalized?	0
#wordsBefore	6
#wordsAfter	3
relativeOffset	0.66
leftWord=about	1
leftWord=best	0
rightWord=rates	1
rightWord=in	0
Wall	1
Street	1
vets	1
best	0
in	0
Wall Street	1
Street vets	1
vets raise	1
...	

- Turns the input into a table of features with real values (often binary: 0 or 1).
- In practice: define feature templates like “leftWord=•” from which specific features are instantiated

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…

token positional features

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Wall	1
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immediately neighboring words

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…	

unigrams

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Feature Extraction

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	$\phi(\mathbf{x})$
bias	1
capitalized?	0
#wordsBefore	6
#wordsAfter	3
relativeOffset	0.66
leftWord=about	1
leftWord=best	0
rightWord=rates	1
rightWord=in	0
Wall	1
Street	1
vets	1
best	0
in	0
Wall Street	1
Street vets	1
vets raise	1
...	

bigrams

- Turns the input into a table of features with real values (often binary: 0 or 1).
- In practice: define feature templates like "leftWord=•" from which specific features are instantiated

Feature Extraction

	$\phi(\mathbf{x})$
bias	1
capitalized?	0
#wordsBefore	6
#wordsAfter	3
relativeOffset	0.66
leftWord=about	1
leftWord=best	0
rightWord=rates	1
rightWord=in	0
Wall	1
Street	1
vets	1
best	0
in	0
Wall Street	1
Street vets	1
vets raise	1
…	

$\mathbf{x}$ = Wall Street vets raise concerns about interest rates , politics

bias feature (≈class prior): value of 1 for every $\mathbf{x}$ so the learned weight will reflect prevalence of the class

- Turns the input into a table of features with real values (often binary: 0 or 1).
- In practice: define feature templates like "leftWord=•" from which specific features are instantiated

Feature Extraction

	$\phi(\mathbf{x})$	$\phi(\mathbf{x}')$
bias	1	1
capitalized?	0	0
#wordsBefore	6	3
#wordsAfter	3	8
relativeOffset	0.66	0.27
leftWord=about	1	0
leftWord=best	0	1
rightWord=rates	1	0
rightWord=in	0	1
Wall	1	0
Street	1	0
vets	1	1
best	0	1
in	0	1
Wall Street	1	0
Street vets	1	0
vets raise	1	0

. . .

$\mathbf{x}$ = Wall Street vets raise concerns about interest rates , politics

$\mathbf{x}'$ = Pet 's best interest in mind , but vets must follow law

- Turns the input into a table of features with real values (often binary: 0 or 1).
- In practice: define feature templates like “leftWord=•” from which specific features are instantiated

Choosing Features

- Supervision means that we don't have to pre-specify the precise relationship between each feature and the classification outcomes.

- But domain expertise helps in choosing which kinds of features to include in the model. (words, subword units, metadata, ...)
  - And sometimes, highly task-specific features are helpful.

- The decision about what features to include in a model is called **feature engineering**.
  - (There are some algorithmic techniques, such as *feature selection*, that can assist in this process.)
  - More features = more flexibility, but also more expensive to train, more opportunity for overfitting.

Linear Model

- For each input $\mathbf{x}$ (e.g., a document or word token), let $\boldsymbol{\phi}(\mathbf{x})$ be a function that extracts a vector of its features.
  - Features may be binary (e.g., `capitalized?`) or real-valued (e.g., `#word=debt`).

- Each feature receives a real-valued **weight** parameter w . Each candidate label y' is scored for the token by summing the weights for the active features:

$$\mathbf{w}_{y'}{}^{\top}\boldsymbol{\phi}(\mathbf{x})$$
$$= \Sigma_j \, w_{y',j} \cdot \phi_j(\mathbf{x})$$

- For binary classification, equivalent to: $\mathrm{sign}(\mathbf{w}^{\top}\boldsymbol{\phi}(\mathbf{x}))$ — $+1$ or -1

	$\phi(\mathbf{x})$	w	$\phi(\mathbf{x}')$
bias	1	−3.00	1
capitalized?	0	.22	0
#wordsBefore	6	−.01	3
#wordsAfter	3	.01	8
relativeOffset	0.6	1.00	0.2
leftWord=about	1	.00	0
leftWord=best	0	−2.00	1
rightWord=rates	1	5.00	0
rightWord=in	0	−1.00	1
Wall	1	1.00	0
Street	1	−1.00	0
vets	1	−.05	1
best	0	−1.00	1
in	0	−.01	1
Wall Street	1	4.00	0
Street vets	1	.00	0
vets raise	1	.00	0

. . .

$\mathbf{x}$ = Wall Street vets raise concerns about interest rates , politics

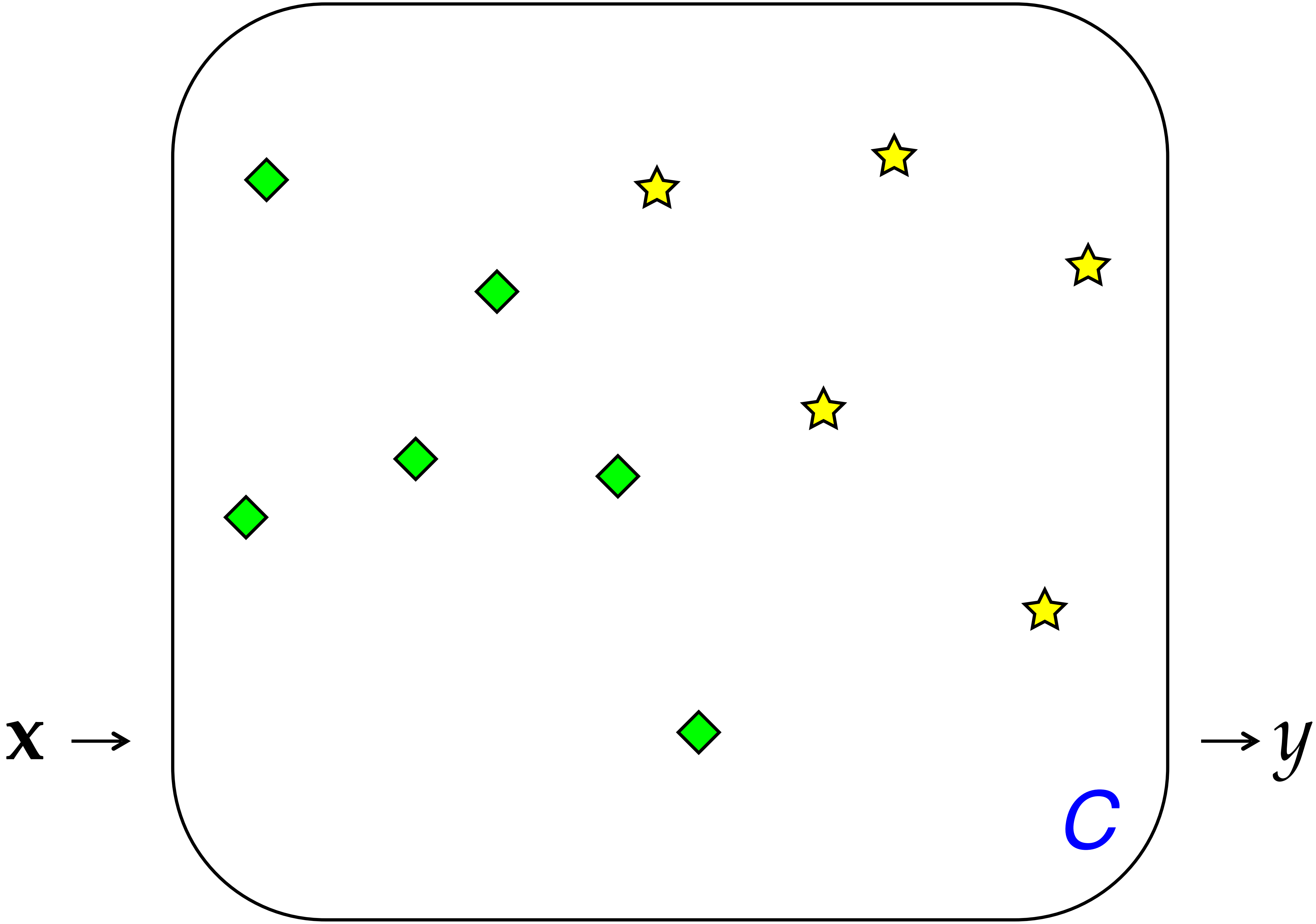
$\mathbf{x}'$ = Pet 's best interest in mind , but vets must follow law

- Weights are learned from data
- For the moment, assume binary classification: financial or nonfinancial
  - More positive weights more indicative of financial.
  - $\mathbf{w}^{\mathsf{T}}\phi(\mathbf{x}) = 6.59$, $\mathbf{w}^{\mathsf{T}}\phi(\mathbf{x}') = -6.74$

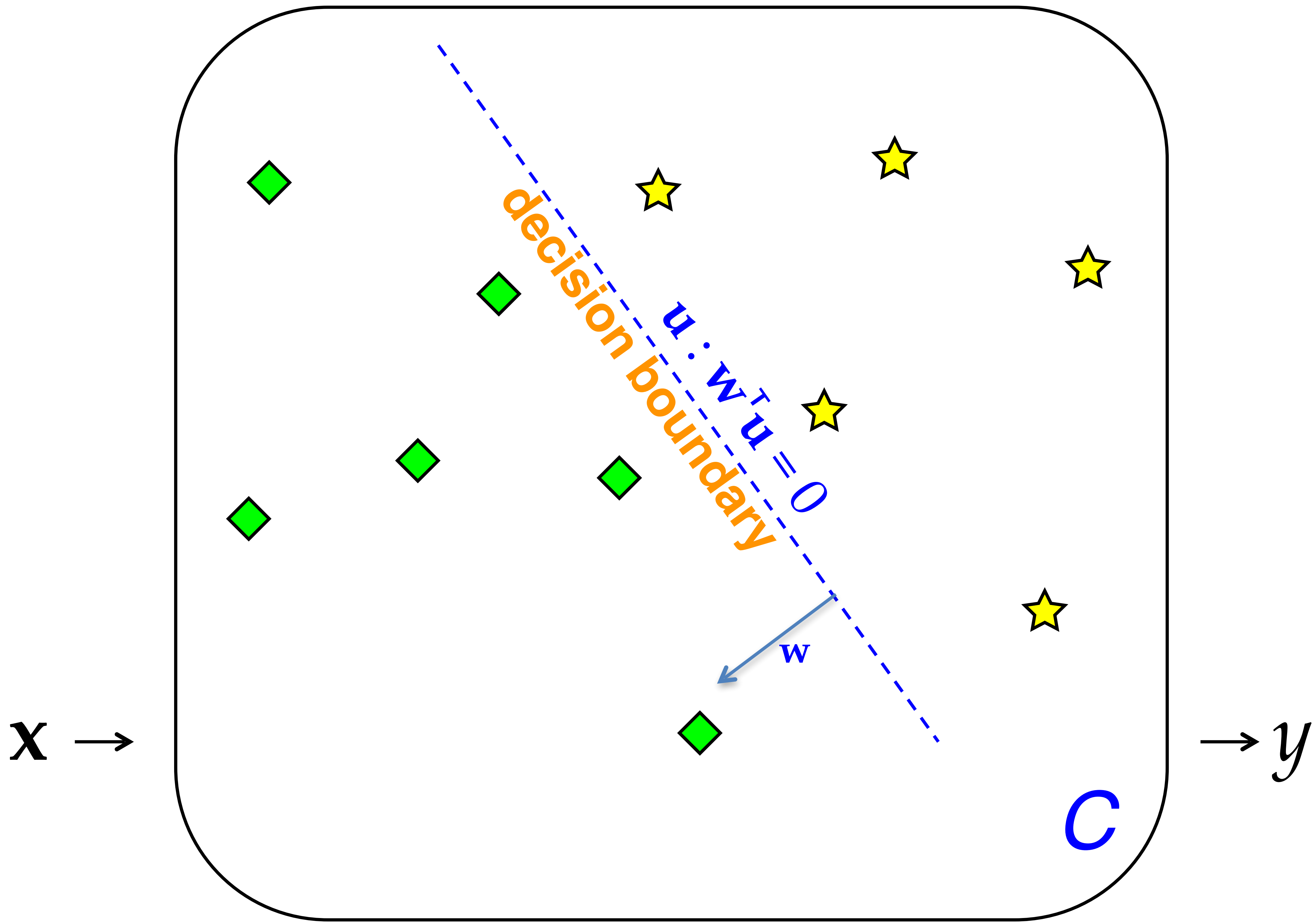
More then 2 classes

- Simply keep a separate weight vector for each label: $\mathbf{w}_y$
- The label y whose weight vector gives the highest score wins!

Linear Classifiers: Geometric View



Linear Classifiers: Geometric View



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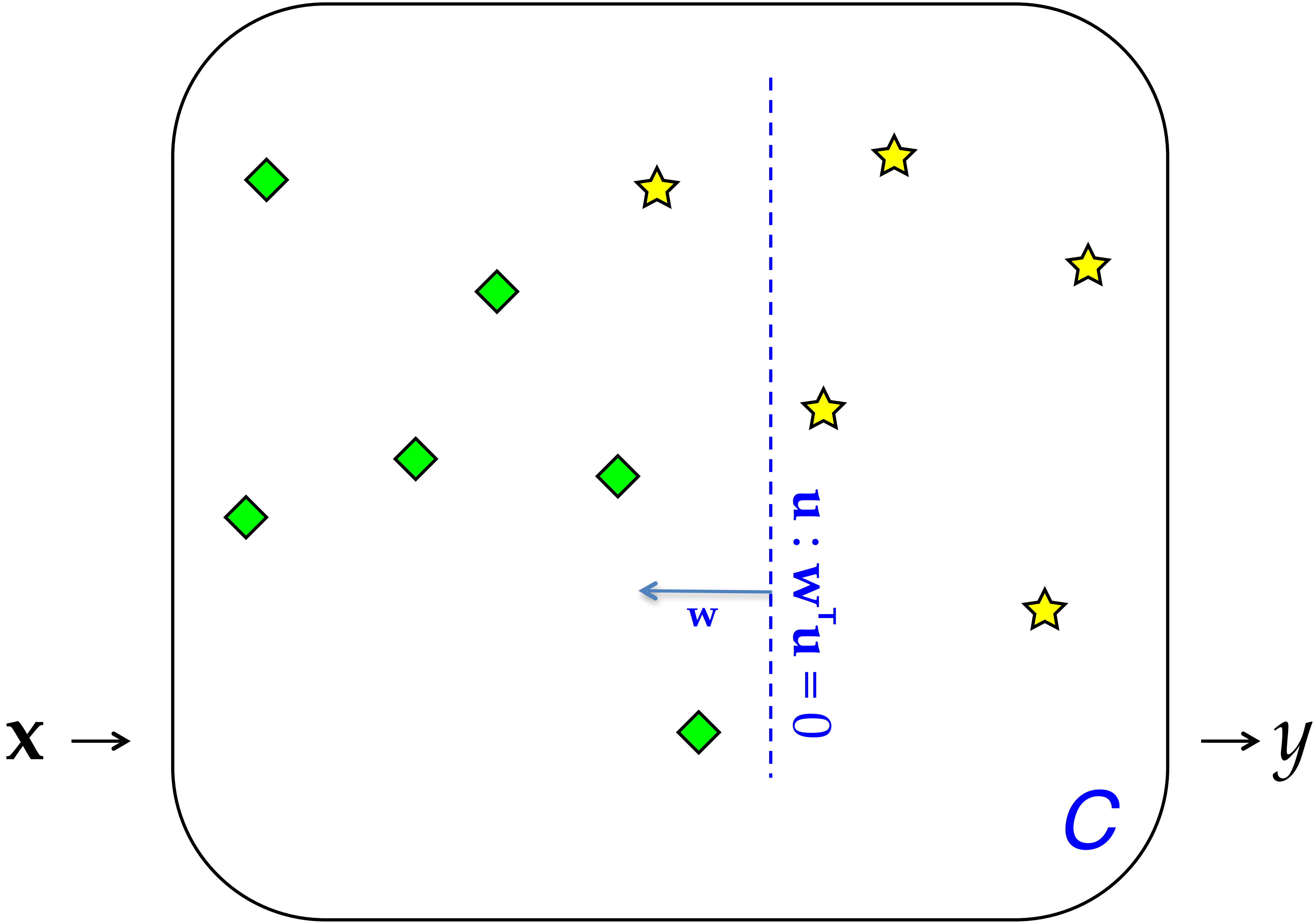
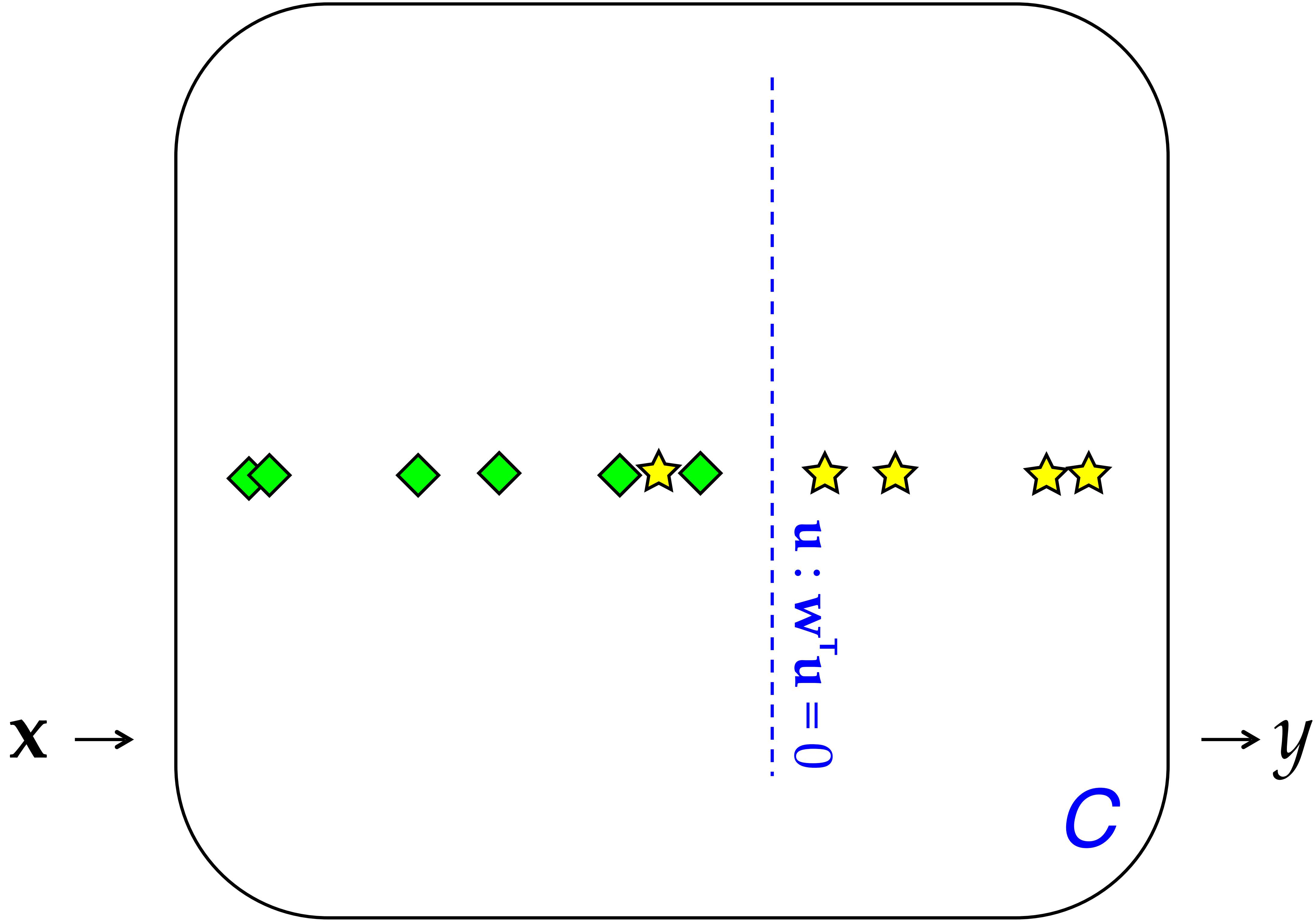


Linear Classifiers: Geometric View



Linear Classifiers (> 2 Classes)

$\mathbf{x} \rightarrow$

return

arg $\max_y \mathbf{w}_y^\top \mathbf{\Phi}(\mathbf{x})$

C

$\rightarrow y$

The term "feature"

- The term "feature" is overloaded in NLP/ML. Here are three different concepts:
  - **Linguistic feature:** in some formalisms, a symbolic property that applies to a unit to categorize it, e.g. [−voice] for a sound in phonology or [+past] for a verb in morphology.
  - **Percept** (or **input feature**)**:** captures some aspect of an input $\mathbf{x}$; binary- or real-valued. *[The term "percept" is nonstandard but I think it is useful!]*

    ends in *-ing*
  - **Parameter** (or **model feature**): an association between some percept and an output class (or structure) y for which a real-valued weight or score is learned.

    ends in *-ing* **∧** y=VERB

Weights

- So far we have just discussed the **classifier**, which relies on weights.

- The weights are determined by a **learner**, which fits them to the training data.

- Naïve Bayes probability estimation can be thought of as learning the weights with bag-of-words features only.

- Several popular learning algorithms for feature-based linear models: **perceptron**, support vector machine (SVM), maximum entropy a.k.a. multiclass logistic regression
  - Deep learning models are **nonlinear**

Evaluating Multiclass Classifiers and Retrieval Algorithms

Accuracy

- Assume we are disambiguating word senses such that every token has 1 gold sense label.
- The classifier predicts 1 label for each token in the test set.
- Thus, every test set token has a predicted label (*pred*) and a gold label (*gold*).
- The **accuracy** of our classifier is just the % of tokens for which the predicted label matched the gold label: $\#_{pred=gold} / \#_{tokens}$

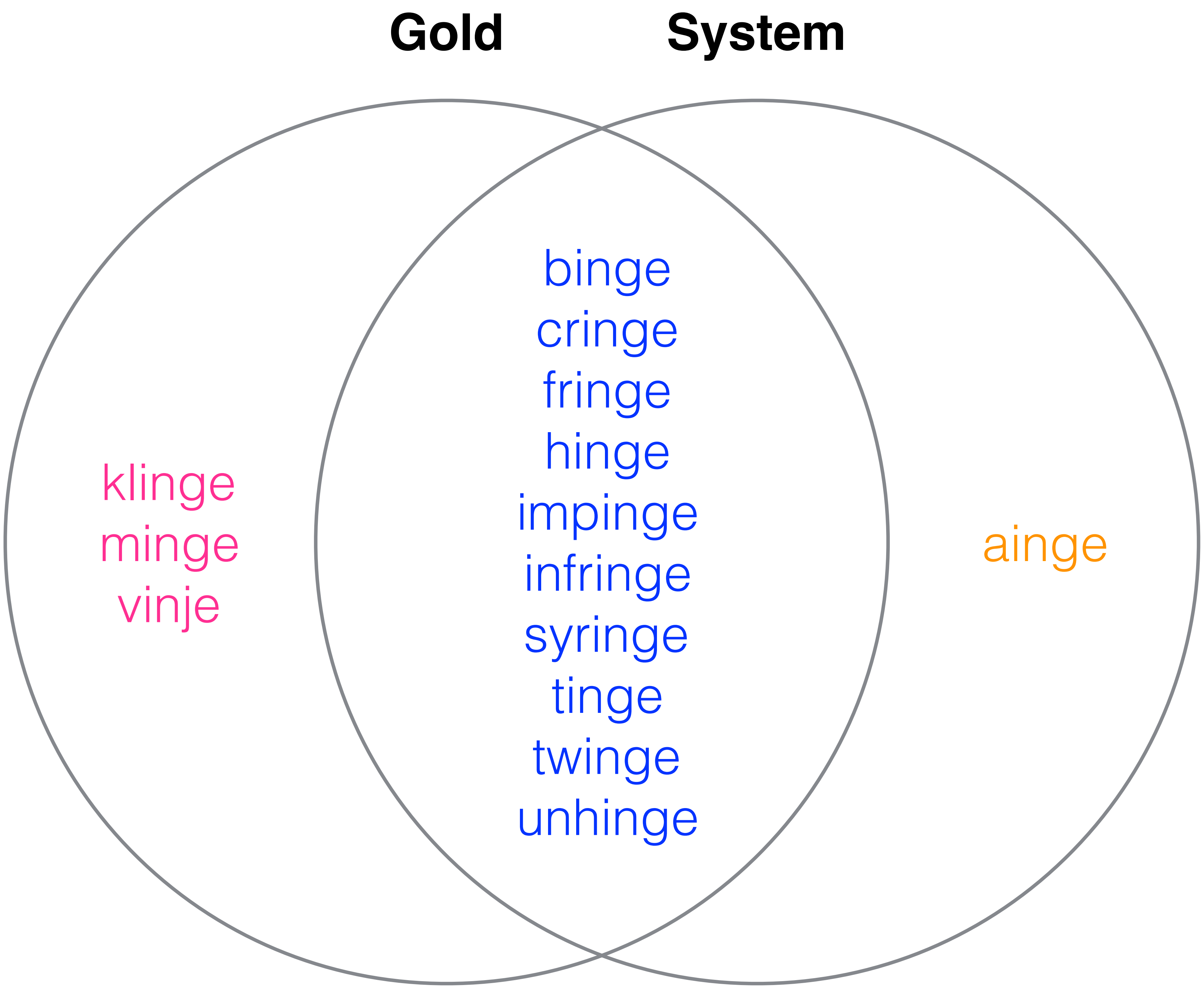
Precision and Recall

- To measure the classifier with respect to a certain label y, and there are >2, we distinguish precision and recall:
  - **precision** = proportion of times the label was predicted and that prediction matched the gold: $\#_{pred=gold=y} / \#_{pred=y}$
  - **recall** = proportion of times the label was in the gold standard and was recovered correctly by the classifier: $\#_{pred=gold=y} / \#_{gold=y}$
- The harmonic mean of precision and recall, called **F_1-score**, balances between the two.
  F_1 = 2*precision*recall / (precision + recall)

Evaluating Retrieval Systems

- Precision/Recall/F-score are also useful for evaluating retrieval systems.
- E.g., consider a system which takes a word as input and is supposed to retrieve all rhymes.
- Now, for a single input (the query), there are often many correct outputs.
- **Precision** tells us whether most of the given outputs were valid rhymes; **recall** tells us whether most of the valid rhymes in the gold standard were recovered.

Rhymes for “hinge”



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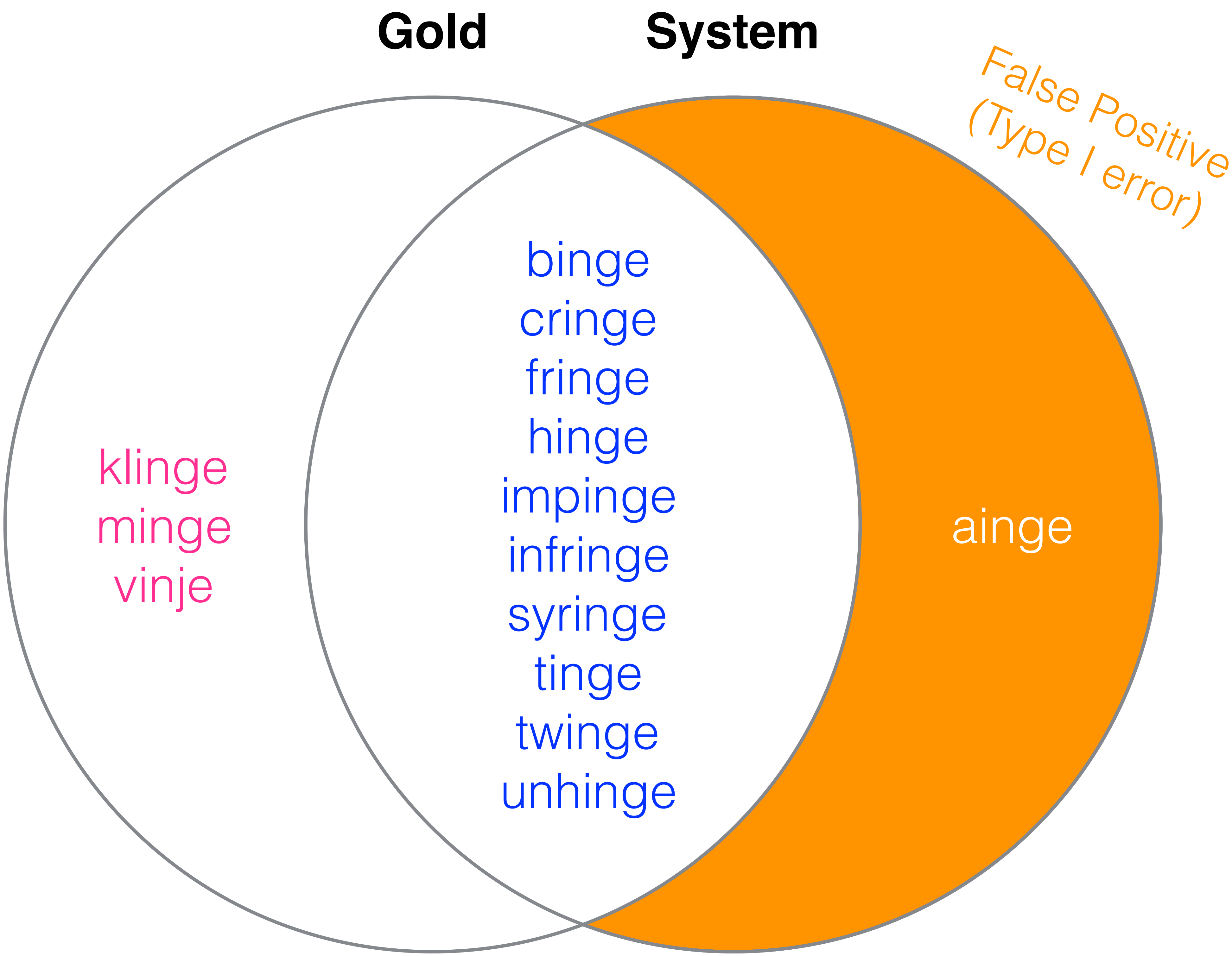

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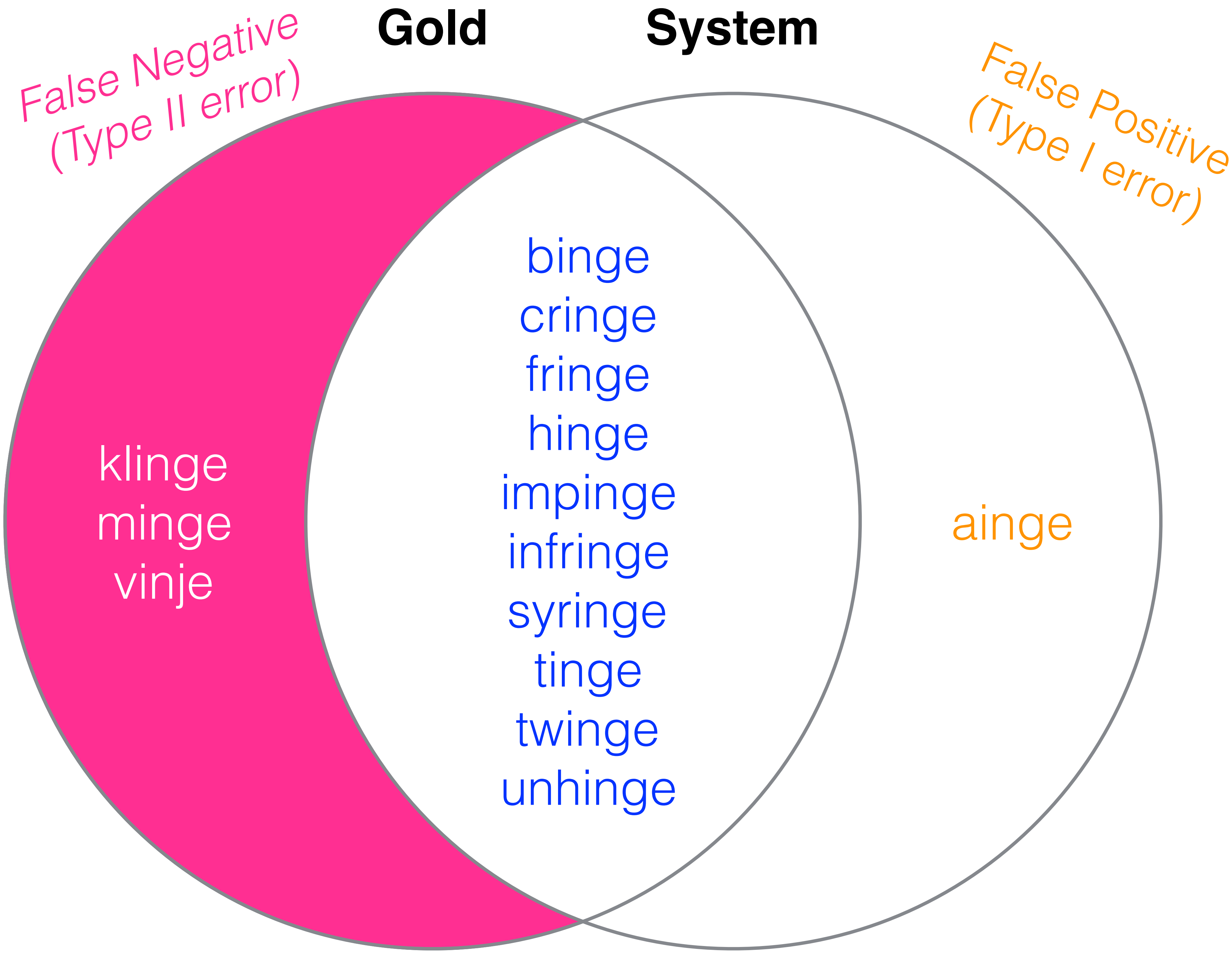

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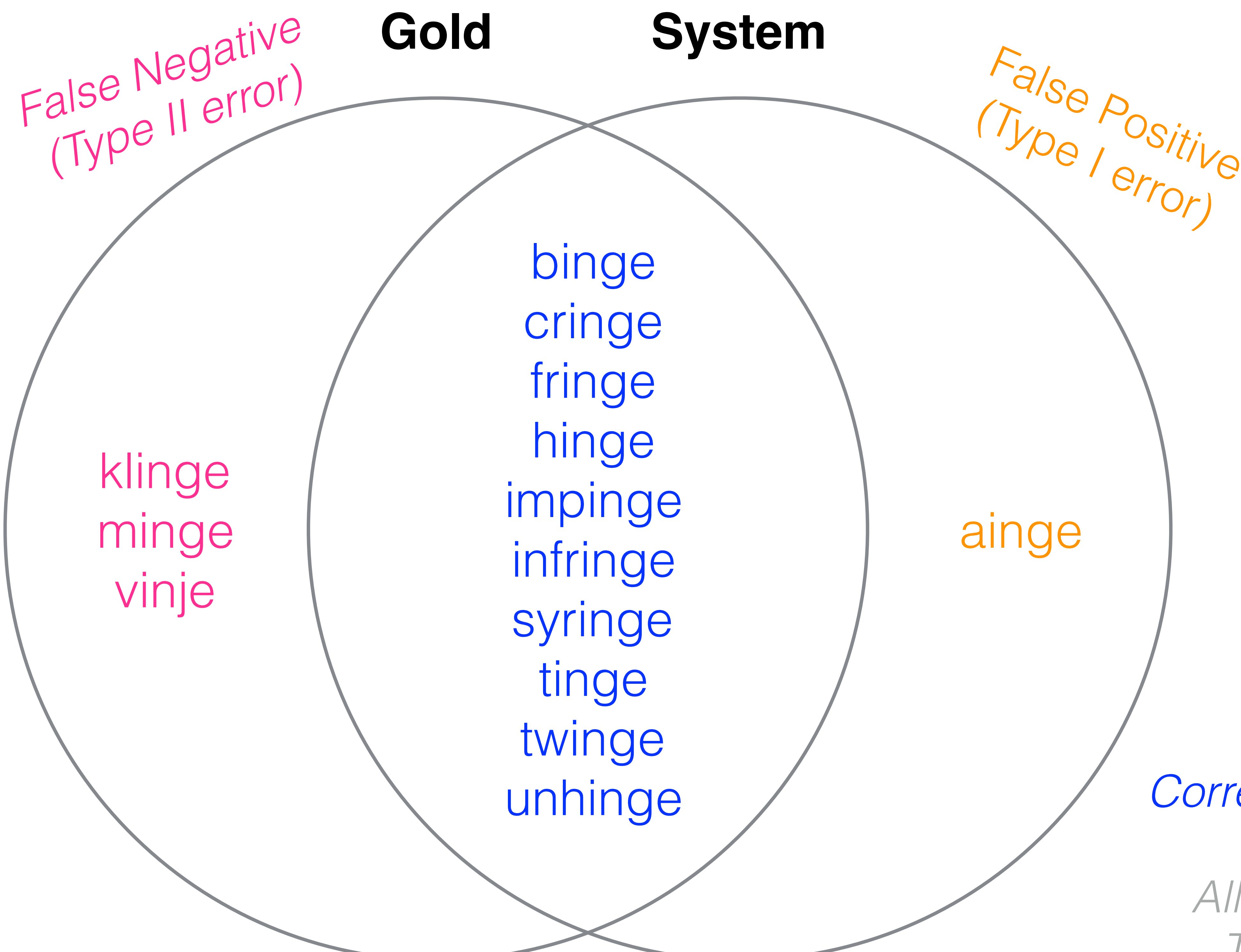
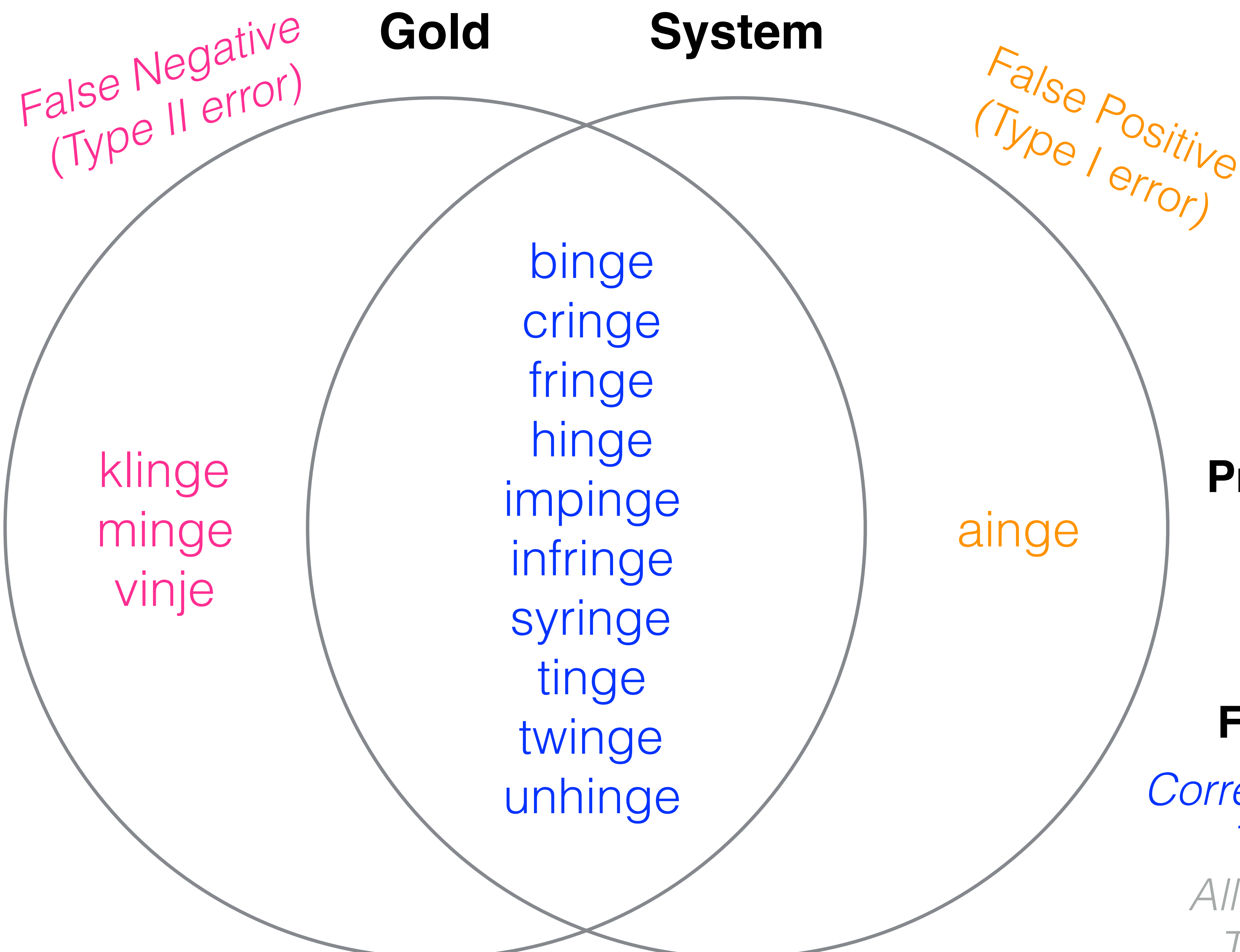


	Sys=Y	Sys=N
Gold=Y	10	3
Gold=N	1	(large)

Correctly predicted = True Positive

All other words = True Negative

Precision & Recall



	Sys=Y	Sys=N
Gold=Y	10	3
Gold=N	1	(large)

Precision = TP/(TP+FP)
= 10/11 = 91%

Recall = TP/(TP+FN)
= 10/13 = 77%

$\mathbf{F_1 = 2 \cdot P \cdot R/(P+R)}$ = 83%

Correctly predicted = True Positive

All other words = True Negative

Perceptron Learner

Perceptron Learner

$\mathbf{X} \rightarrow$

$\mathbf{Y} \rightarrow$

$\mathbf{w} \leftarrow \mathbf{0}$

for i = 1 … I:

  for t = 1 … T:

    select $(\mathbf{x}, y)_t$

    # run current classifier

    $\hat{y} \leftarrow \arg\max_{y'} \mathbf{w}_{y'}^{\top} \boldsymbol{\Phi}(\mathbf{x})$

    if $\hat{y} \neq y$ then *# mistake*

      $\mathbf{w}_y \leftarrow \mathbf{w}_y + \boldsymbol{\Phi}(\mathbf{x})$

      $\mathbf{w}_{\hat{y}} \leftarrow \mathbf{w}_{\hat{y}} - \boldsymbol{\Phi}(\mathbf{x})$

return $\mathbf{w}$

L

$\rightarrow$ $\mathbf{w}$

(assumes all classes have the same **percepts**)

Perceptron Learner

$\mathbf{X} \rightarrow$

$\mathbf{Y} \rightarrow$

$\mathbf{w} \leftarrow \mathbf{0}$

for i = 1 … I:

  for t = 1 … T:

    select $(\mathbf{x}, y)_t$

    # run current classifier

    $\hat{y} \leftarrow$ C $\leftarrow \mathbf{x}$

decoding is a subroutine of learning

    if $\hat{y} \neq y$ then *# mistake*

      $\mathbf{w}_y \leftarrow \mathbf{w}_y + \mathbf{\Phi}(\mathbf{x})$

      $\mathbf{w}_{\hat{y}} \leftarrow \mathbf{w}_{\hat{y}} - \mathbf{\Phi}(\mathbf{x})$

return $\mathbf{w}$

L

$\rightarrow$ $\mathbf{w}$

(assumes all classes have the same **percepts**) work through example on the board

Perceptron Learner

- **The perceptron doesn't estimate probabilities.** It just adjusts weights up or down until they classify the training data correctly.
  - No assumptions of feature independence necessary! ⇒ Better accuracy than NB

- The perceptron is an example of an **online** learning algorithm because it potentially updates its parameters (weights) with each training datapoint.

- Classification, a.k.a. **decoding**, is called with the latest weight vector. Mistakes lead to weight updates.

- One hyperparameter: I, the number of iterations (passes through the training data).

- Often desirable to make several passes over the training data. The number can be tuned. Under certain assumptions, it can be proven that the learner will converge.

Perceptron: Avoiding overfitting

- Like any learning algorithm, the perceptron risks overfitting the training data. Two main techniques to improve generalization:
  - **Averaging:** Keep a copy of each weight vector as it changes, then average all of them to produce the final weight vector. Daumé chapter has a trick to make this efficient with large numbers of features.
  - **Early stopping:** Tune I by checking held-out accuracy on dev data (or cross-val on train data) after each iteration. If accuracy has ceased to improve, stop training and use the model from iteration $I-1$.

Generative vs. Discriminative

- Naïve Bayes allows us to classify via the **joint probability** of $\mathbf{x}$ and y:
  - $\mathrm{p}(y \mid \mathbf{x}) \propto \mathrm{p}(y)\, \Pi_{w \in \mathbf{x}}\, \mathrm{p}(w \mid y)$
    $= \mathrm{p}(y)\, \mathrm{p}(\mathbf{x} \mid y)$ (per the independence assumptions of the model)
    $= \mathrm{p}(y, \mathbf{x})$ (chain rule)
  - This means the model accounts for BOTH **x** and *y*. From the joint distribution p(**x**,*y*) it is possible to compute p(**x**) as well as p(*y*), p(**x** | *y*), and p(*y* | **x**).
- NB is called a **generative** model because it assigns probability to linguistic objects (**x**). It could be used to generate "likely" language corresponding to some *y*. (Subject to its naïve modeling assumptions!)
  - (Not to be confused with the "generative" school of linguistics.)
- Some other linear models, including the perceptron, are **discriminative**: they are trained directly to classify given **x**, and cannot be used to estimate the probability of **x** or generate **x** | *y*.

Take-home points

- Feature-based linear classifiers are important to NLP.
  - You define the features, an algorithm chooses the weights.
    - The weights are real-valued.
    - Some classifiers, like **logistic regression**, are probabilistic: the weights correspond to probabilities.
  - More features ⇒ more flexibility, also more risk of overfitting. Because we work with large vocabularies, not uncommon to have millions of features.
- Some models, like Naïve Bayes, have a closed-form solution for parameters. Learning is cheap!
- The **perceptron** and other discriminative methods require fancier learning/ optimization algorithms that iterate multiple times over the data, adjusting parameters until convergence (or some other stopping criterion).
  - The advantage: fewer modeling assumptions. Weights can be interdependent. **Discriminative** methods usually achieve higher accuracy with sufficient training data and computation (optimization).

Which classifier to use?

- Fast and simple: **naïve Bayes**
- Very accurate, still simple: **perceptron**
- Very accurate, probabilistic, more complicated to implement: **MaxEnt**
- Potentially best accuracy, more complicated to implement: **SVM**
- All of these: watch out for **overfitting**! (NB—smoothing; Perceptron—early stopping, averaging; MaxEnt—regularization)
- Check the web for free and fast implementations, e.g. SVM^{light}

Further Reading: Basics & Examples

- **Manning:** features in linear classifiers
  http://www.stanford.edu/class/cs224n/handouts/MaxentTutorial-16x9-FeatureClassifiers.pdf

- **Goldwater:** naïve Bayes & MaxEnt examples
  http://www.inf.ed.ac.uk/teaching/courses/fnlp/lectures/07_slides.pdf

- **O'Connor:** MaxEnt—incl. step-by-step examples, comparison to naïve Bayes
  http://people.cs.umass.edu/~brenocon/inlp2015/04-logreg.pdf

- **Daumé:** "The Perceptron" (*A Course in Machine Learning*, ch. 3)
  http://www.ciml.info/dl/v0_8/ciml-v0_8-ch03.pdf

- **Neubig:** "The Perceptron Algorithm"
  http://www.phontron.com/slides/nlp-programming-en-05-perceptron.pdf

Further Reading: Advanced

- **Neubig:** “Advanced Discriminative Learning”—MaxEnt w/ derivatives, SGD, SVMs, regularization
  http://www.phontron.com/slides/nlp-programming-en-06-discriminative.pdf
- **Manning:** generative vs. discriminative, MaxEnt likelihood function and derivatives
  http://www.stanford.edu/class/cs224n/handouts/MaxentTutorial-16x9-MEMMs-Smoothing.pdf, slides 3–20
- **Daumé:** linear models
  http://www.ciml.info/dl/v0_8/ciml-v0_8-ch06.pdf
- **Smith:** A variety of loss functions for text classification
  http://courses.cs.washington.edu/courses/cse517/16wi/slides/tc-intro-slides.pdf & http://courses.cs.washington.edu/courses/cse517/16wi/slides/tc-advanced-slides.pdf