Information Extraction

Lecture 6 – Linear Models (Basic Machine Learning)

CIS, LMU München

Winter Semester 2019-2020

Prof. Dr. Alexander Fraser, CIS

Decision Trees vs. Linear Models

- Decision Trees are an intuitive way to learn classifiers from data
  - They fit the training data well
  - With heavy pruning, you can control overfitting
- NLP practitioners often use linear models instead
- Most of the models discussed in Sarawagi Chapter 3 are linear models

Decision Trees for NER

- So far we have seen:
  - How to learn rules for NER
  - A basic idea of how to formulate NER as a classification problem
  - Decision trees
    - Including the basic idea of **overfitting** the training data
- How can we use decision trees for NER?

Rule Sets as Decision Trees

- Decision trees are quite powerful
- It is easy to see that complex rules can be encoded as decision trees
- For instance, let's go back to border detection in CMU seminars...

… the Seminar at <stime> 4 pm will …

Position	Condition	Context-independent features			Context Dep.	Action
	Word	**Lemma**	**Capitalization**	**SemCat**	**POS**	
-3						
-2						
-1		**at**				**stime**
+1					**Digit**	
+2				**timeid**		
+3						

Example modified from Ciravegna 2009

A Path in the Decision Tree

- The tree will check if the token to the left of the possible start position has "at" as a lemma
- Then check if the token after the possible start position is a Digit
- Then check the second token after the start position is a timeid ("am", "pm", etc)
- If you follow this path at a particular location in the text, then the decision should be to insert a <stime>

Linear Models

- However, in practice decision trees are not used so often in NLP
- Instead, linear models are used
- Let me first present linear models
- Then I will compare linear models and decision trees

Binary Classification

- I'm going to first discuss linear models for binary classification, using binary features
- We'll take the same scenario as before
- Our classifier is trying to decide whether we have a <stime> tag or not at the current position (between two words in an email)
- The first thing we will do is encode the context at this position into a feature vector

Feature Vector

- Each feature is true or false, and has a position in the feature vector
- The feature vector is typically sparse, meaning it is mostly zeros (i.e., false)
- The feature vector represents the full feature space. For instance, consider...

… the Seminar at <stime> 4 pm will …

Position	Condition	Context-independent features			Context Dep.	Action
	Word	**Lemma**	**Capitalization**	**SemCat**	**POS**	
-3	the	the	lowercase		Art	
-2	Seminar	seminar	uppercase		Noun	
-1	at	at	lowercase		Prep	**stime**
+1	4	4	lowercase		Digit	
+2	pm	pm	lowercase	timeid	Other	
+3	will	will	lowercase		Verb	

Example modified from Ciravegna 2009

… the Seminar at <stime> 4 pm will …

Position	Condition	Context-independent features			Context Dep.	Action
	Word	**Lemma**	**Capitalization**	**SemCat**	**POS**	
-3	the	the	lowercase		Art	
-2	Seminar	seminar	uppercase		Noun	
-1	at	at	lowercase		Prep	**stime**
+1	4	4	lowercase		Digit	
+2	pm	pm	lowercase	timeid	Other	
+3	will	will	lowercase		Verb	

Example modified from Ciravegna 2009

5

- Our features represent this table using binary variables
- For instance, consider the lemma column
- Most features will be false (false = off = 0)
- The lemma features that will be on (true = on = 1) are:

  -3_lemma_the
  -2_lemma_Seminar
  -1_lemma_at
  +1_lemma_4
  +2_lemma_pm
  +3_lemma_will

Classification

- To classify we will take the dot product of the feature vector with a learned weight vector
- We will say that the class is true (i.e., we should insert a <stime> here) if the dot product is > 0, and false otherwise
- Because we might want to shift the decision boundary, we add a feature that is always true
  - This is called the bias
  - By weighting the bias, we can shift where we make the decision (see next slide)

Feature Vector

- We might use a feature vector like this:

(this example is simplified – really we'd have all features for all positions)

1	Bias term
0	... (say, -3_lemma_giraffe)
1	-3_lemma_the
0	...
1	-2_lemma_Seminar
0	...
0	...
1	-1_lemma_at
1	+1_lemma_4
0	...
1	+1_Digit
1	+2_timeid

Weight Vector

- Now we'd like the dot product to be > 0 if we should insert a <stime> tag
- To encode the rule we looked at before we have three features that we want to have a positive weight
  - -1_lemma_at
  - +1_Digit
  - +2_timeid
- We can give them weights of 1
- Their sum will be three
- To make sure that we only classify if all three weights are on, let's set the weight on the bias term to -2

Dot Product - I

1	Bias term	-2
0		0
1	-3_lemma_the	0
0		0
1	-2_lemma_Seminar	0
0		0
0		0
1	-1_lemma_at	1
1	+1_lemma_4	0
0		0
1	+1_Digit	1
1	+2_timeid	1

To compute the dot product first take the product of each row, and then sum these

Dot Product - II

1	Bias term	-2	1*-2	1*-2
0		0	0*0	
1	-3_lemma_the	0	0*0	
0		0	0*0	
1	-2_lemma_Seminar	0	1*0	
0		0	0*0	
0		0	0*0	
1	-1_lemma_at	1	1*1	1*1
1	+1_lemma_4	0	1*0	
0		0	0*0	
1	+1_Digit	1	1*1	1*1
1	+2_timeid	1	1*1	1*1

				1

Learning the Weight Vector

- The general learning task is simply to find a good weight vector!
  - This is sometimes also called "training"
- Basic intuition: you can check weight vector candidates to see how well they classify the training data
  - Better weights vectors get more of the training data right
- So we need some way to make (smart) changes to the weight vector
  - The goal is to make better decisions on the training data
- I will talk more about this later

Feature Extraction

- We run **feature extraction** to get the feature vectors for each position in the text
- We typically use a text representation to represent true values (which are sparse)
- Often we define **feature templates** which describe the feature to be extracted and give the name of the feature (i.e., -1_lemma_ XXX)

-3_lemma_the -2_lemma_Seminar -1_lemma_at +1_lemma_4 +1_Digit +2_timeid	STIME
-3_lemma_Seminar -2_lemma_at -1_lemma_4 -1_Digit +1_timeid +2_lemma_ will	NONE

...

Training vs. Testing

- When training the system, we have gold standard labels (see previous slide)
- When testing the system on new data, we have no gold standard
  - We run the same feature extraction first
  - Then we take the dot product with the weight vector to get a classification decision
- Finally, we have to go back to the original text to write the <stime> tags into the correct positions

Summary so far

- So we've seen training and testing
- We have an idea about train error and test error (key concepts!)
- We are aware of the problem of overfitting
  - And we know what overfitting means in terms of train error and test error!

- Now let's compare decision trees and linear models

Linear models are weaker

- Linear models are weaker than decision trees
  - This means they can't express the same richness of decisions as decision trees can (if both have access to the same features)
- It is easy to see this by extending our example
- Recall that we have a weight vector encoding our rule (see next slide)
- Let's take another reasonable rule

… the Seminar at <stime> 4 pm will …

Position	Condition	Context-independent features			Context Dep.	Action
	Word	**Lemma**	**Capitalization**	**SemCat**	**POS**	
-3	the	the	lowercase		Art	
-2	Seminar	seminar	uppercase		Noun	
-1	at	at	lowercase		Prep	**stime**
+1	4	4	lowercase		Digit	
+2	pm	pm	lowercase	timeid	Other	
+3	will	will	lowercase		Verb	

Example modified from Ciravegna 2009

… the Seminar at <stime> 4 pm will …

Position	Condition	Context-independent features			Context Dep.	Action
	Word	**Lemma**	**Capitalization**	**SemCat**	**POS**	
-3						
-2						
-1		**at**				**stime**
+1					**Digit**	
+2				**timeid**		
+3						

Example modified from Ciravegna 2009

- The rule we'd like to learn is that if we have the features:
  - -2_lemma_seminar
  - -1_lemma_at
  - +1_Digit
- We should insert a <stime>
- This is quite a reasonable rule, it lets us correctly cover the new sentence:

  "The Seminar at 3 will be given by ..."

  (there is no timeid like "pm" here!)
- Let's modify the weight vector

Adding the second rule

1	Bias term	-2
0		0
1	-3_lemma_the	0
0		0
1	-2_lemma_Seminar	1
0		0
0		0
1	-1_lemma_at	1
1	+1_lemma_4	0
0		0
1	+1_Digit	1
1	+2_timeid	1

- Let's first verify that both rules work with this weight vector
- But does anyone see any issues here?

How many rules?

- If we look back at the vector, we see that we have actually encoded quite a number of rules
  - Any combination of three features with ones will be sufficient so that we have a <stime>
  - This might be good (i.e., it might generalize well to other examples). Or it might not.
- But what is definitely true is that it would be easy to create a decision tree that only encodes exactly our two rules!
- This should give you an intuition as to how linear models are weaker than decision trees
- Linear models are used heavily in NLP exactly because they are weaker, since being weaker means they have less problems with overfitting
  - This is particularly important in NLP problems because often NLP researchers like to use a very large number of features (which might lead to really huge decision trees)

How can we get this power in linear models?

- Change the features!
- For instance, we can create combinations of our old features as new features
- For instance, clearly if we have:
  - One feature to encode our first rule
  - Another feature to encode our second rule
  - And we set the bias to 0
- We now get the same as the decision tree
- Sometimes these new compound features would be referred to as trigrams (they each combine three basic features)

Feature Selection

- A task which includes automatically finding such new compound features is called **feature selection**
  - This is built into some machine learning toolkits
  - Or you can implement it yourself by trying out feature combinations and checking the training error
    - Use human intuition to check a small number of combinations
    - Or do it automatically, using a script

Training

Training is **automatically adjusting** the feature vector so as to better fit the training corpus! **Intuition: make small adjustments** to get a better score on the training data (these all fit our example!)

$$
\begin{bmatrix} -2 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}
\quad
\begin{bmatrix} -2.01 \\ 0.04 \\ 0.0004 \\ 0 \\ 1.1 \\ 0 \\ 0 \\ 0.9001 \\ 0 \\ 0 \\ 0.89 \\ 0.91 \end{bmatrix}
\quad
\begin{bmatrix} -1.99 \\ 0.04 \\ 0.002 \\ 0 \\ 1.101 \\ 0 \\ 0 \\ 0.9111 \\ 0 \\ 0 \\ 0.892 \\ 0.91 \end{bmatrix}
\quad
\begin{bmatrix} -2.01 \\ 0.043 \\ 0.0003 \\ 0 \\ 1.1 \\ 0 \\ 0 \\ 0.9144 \\ 0 \\ 0 \\ 0.93 \\ 1.01 \end{bmatrix}
$$

Perceptron Update I

- One way to do this is using a so-called **perceptron**

- Algorithm:
- Read the training examples one at a time
- For each training example, decide how to update the weight vector
- The perceptron update rule says:
  - If a training example is classified correctly:
    - Do nothing (because the current weight vector is fine)
  - If a training example is classified incorrectly:
    - Adjust the weight of every active feature by a small amount towards the desired decision
    - So that the example will score a bit better next time it is observed
- Intuition: we hope that by making many small changes
  - The weights on important features increase consistently to the desired values which work well on the entire training set
  - The changes to unimportant feature weights will be random (sometimes up, sometimes down), and the weights will tend towards zero (meaning: no effect on the classification)

Perceptron Update II

Say we have -2 0 0 0 ... 0 0 0 0.5, and see this training example. Clearly we will get it wrong...

1	Bias term	-2	1*-2	-2
0		0		
1	-3_lemma_the	0		
0		0		
1	-2_lemma_Seminar	0		
0		0		
0		0		
1	-1_lemma_at	0		
1	+1_lemma_4	0		
0		0		
1	+1_Digit	0		
1	+2_timeid	0.5	1*0.5	0.5

				-1.5

Perceptron Update III

So change the weight vector, by adding 0.1 to all active features. Score is now better (but still wrong)

1	Bias term	-1.9	1*-1.9	-1.9
0		0		
1	-3_lemma_the	0.1	1*0.1	0.1
0		0		
1	-2_lemma_Seminar	0.1	1*0.1	0.1
0		0		
0		0		
1	-1_lemma_at	0.1	1*0.1	0.1
1	+1_lemma_4	0.1	1*0.1	0.1
0		0		
1	+1_Digit	0.1	1*0.1	0.1
1	+2_timeid	0.6	1*0.6	0.6

				-0.8

Perceptron Update IV

After looking at many other examples, irrelevant features (like "-3_lemma_the") are pushed back towards zero, and important features have stronger weights.

We have learned a good weight vector for this example, no further update is needed

1	Bias term	-2.1	1*-2.1	-2.1
0		0		
1	-3_lemma_the	-0.1	1*-0.1	-0.1
0		0		
1	-2_lemma_Seminar	0.1	1*0.1	0.1
0		0		
0		0		
1	-1_lemma_at	0.7	1*0.7	0.7
1	+1_lemma_4	0		
0		0		
1	+1_Digit	1.1	1*1.1	1.1
1	+2_timeid	1.2	1*1.2	1.2

				0.9

Word embeddings

- Word embeddings such as the popular word2vec embeddings are a clever way to get better features
  - Word embeddings are learned on huge amounts of text
  - Details in next week's lecture
- Word-types are represented as positions in a 50-dimensional space
  - For each word-type, we look up its embedding in a table
- Similar words are close to each other in this space, for instance:
  - AM and PM (words for which SemCat=timeid) will have very similar representations
  - Different words with the same lemma will have very similar representations
- So when using word embeddings, we do not need the context-independent features
  - And the embedding space captures many generalizations about word-types that we didn't actively know would help!
  - These generalizations become available to the learner, which can choose to use them if they are helpful for learning the training data

… the Seminar at <stime> 4 pm will …

Position	Condition	50-dimen. word-type embeddings (only 3 dimensions shown)			Context Dep.	Action
	Word	**Dim 1**	**Dim 2**	**Dim 3 …**	**POS**	
-3	the	-0.234	0.155	0.001	Art	
-2	Seminar	0.555	0.888	0.002	Noun	
-1	at	-0.165	-0.122	0.001	Prep	**stime**
+1	4	0.122	0.095	-0.003	Digit	
+2	pm	0.001	0.001	**0.999**	Other	
+3	will	-0.812	0.201	0.002	Verb	

Contextualized embeddings

- Contextualized word embeddings allow us to get a different representation of each word token, rather than word-type
  - The entire sentence is used as context
  - Some popular contextualized embeddings are ELMO and BERT
- Contextualized word embeddings capture the same information as word-type embeddings
- But they additionally capture features that are context-dependent
- Makes many more generalizations available to the learner!
  - Part-of-Speech (POS) distinctions will be accessible (as in our example)
  - Polysemy, tokens of a word-type with the same word sense will have similar embeddings
  - Syntactic positions will be captured (e.g., Subject, Verb, Object)
  - Semantic roles will also be captured (e.g., Agent, Patient in a passive sentence)
  - Etc.
- Typically something like 400 dimensional vectors for each word token
  - Input for computing the word-token embeddings is the entire sentence

Two classes

- So far we discussed how to deal with a single label
  - At each position between two words we are asking whether there is a <stime> tag
- This is called **binary classification**
- However, we are interested in <stime> and </stime> tags
- How can we deal with this?
- We can simply train one classifier on the <stime> prediction task
  - Here we are treating </stime> positions like every other non <stime> position
- And train another classifier on the </stime> prediction task
  - Likewise, treating <stime> positions like every other non </stime> position
- If both classifiers predict "true" for a single position, take the one that has the highest dot product

More than two labels

- We can generalize this idea to many possible labels
- This is called **multiclass classification**
    - We are picking one label (class) from a set of classes
- For instance, maybe we are also interested in the <etime> and </etime> labels
    - These labels indicate seminar end times, which are also often in the announcement emails (see next slide)

CMU Seminars - Example

<0.24.4.93.20.59.10.jgc+@NL.CS.CMU.EDU (Jaime Carbonell).0>
Type: cmu.cs.proj.mt
Topic: <speaker>Nagao</speaker> Talk
Dates: 26-Apr-93
Time: <stime>10:00</stime> - <etime>11:00 AM</etime>
PostedBy: jgc+ on 24-Apr-93 at 20:59 from NL.CS.CMU.EDU (Jaime Carbonell)

Abstract:

<paragraph><sentence>This Monday, 4/26, <speaker>Prof. Makoto Nagao</speaker> will give a seminar in the <location>CMT red conference room</location> <stime>10</stime>-<etime>11am</etime> on recent MT research results</sentence>.</paragraph>

One against all

- We can generalize the way we handled two binary classification decisions to many labels
- Let's add the <etime> and </etime> labels
- We can train a classifier for each tag
  - Just as before, every position that is not an <etime> is a negative example for the <etime> classifier, and likewise for </etime>
- If multiple classifiers say "true", take the classifier with the highest dot product
- This is called **one-against-all**
- It is a quite reasonable way to use binary classification to predict one of multiple classes
  - It is not the only option, but it is easy to understand (and to implement too!)

Summary: Multiclass classification

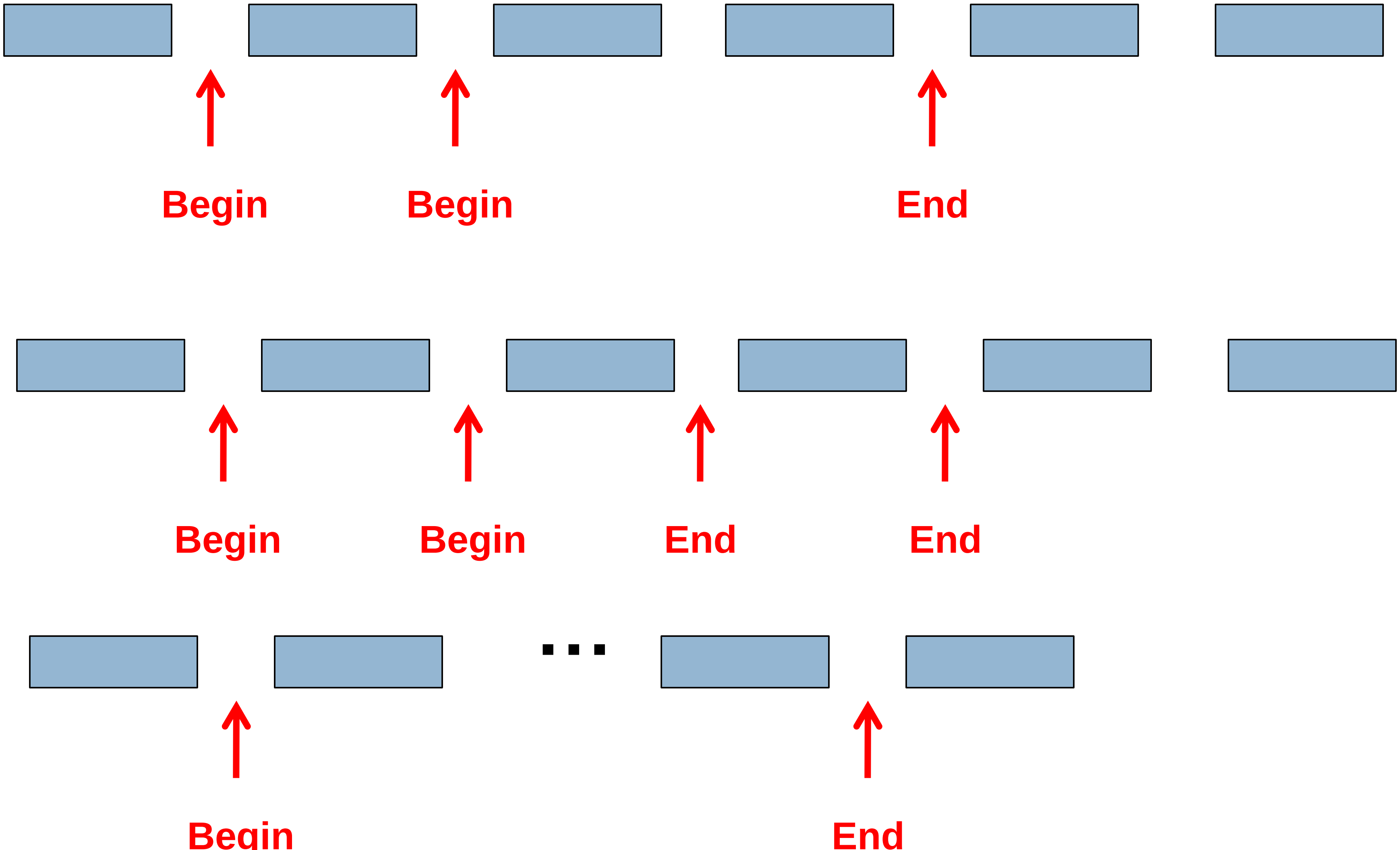
- We discussed **one-against-all**, a framework for combining binary classifiers
- It is not the only way to do this, but it often works pretty well
  - There are also techniques involving building classifiers on different subsets of the data and voting for classes
  - And other techniques can involve, e.g., a sequence of classification decisions (for instance, a tree-like structure of classifications)

Binary classifiers and sequences

- As we saw a few lectures ago, we can detect seminar start times by using two binary classifiers:
  - One for <stime>
  - One for </stime>
- And recall that if they both say "true" to the same position, take the highest dot product

- Then we need to actually annotate the document
- But this is problematic...

Some concerns



Slide from Kauchak

A basic approach

- One way to deal with this is to use a greedy algorithm
- Loop:
  - Scan the document until the <stime> classifier says true
  - Then scan the document until the </stime> classifier says true
- If the last tag inserted was <stime> then insert a </stime> at the end of the document
- Naturally, there are smarter algorithms than this that will do a little better
- But the major problem here is more basic.
  - Relying on these two **independent** classifiers is not optimal!

How can we deal better with sequences?

- We can make our classification decisions dependent on previous classification decisions
- For instance, think of the Hidden Markov Model as used in POS-tagging
- The probability of a verb increases after a noun

Basic Sequence Classification

- We will do the following
  - We will add a feature template into each classification decision representing the **previous classification decision**
  - And we will change the labels we are predicting, so that in the span between a start and end boundary we are predicting a different label than outside

Basic idea

Seminar at 4 pm
<stime> in-stime </stime>

- The basic idea is that we want to use the previous classification decision
- We add a special feature template -1_label_XXX
- For instance, between 4 and pm, we have:
  -1_label_<stime>

- Suppose we have learned reasonable classifiers
- How often should we get a <stime> classification here? (Think about the training data in this sort of position)

-1_label_<stime>

- This should be an extremely strong indicator not to annotate a <stime>
- What else should it indicate?
  - It should indicate that there must be either a in-stime or a </stime> here!

Changing the problem slightly

- We'll now change the problem to a problem of annotating tokens (rather than annotating boundaries)
- This is traditional in IE, and you'll see that it is slightly more powerful than the boundary style of annotation
- We also make less decisions (see next slide)

IOB markup

Seminar	at	4	pm	will	be	on	…
O	O	B-stime	I-stime	O	O	O	

- This is called IOB markup (or BIO = begin-in-out)
- This is a standardly used markup when modeling IE problems as sequence classification problems

- We can use a variety of models to solve this problem
- One popular model is the Hidden Markov Model, which you have seen in Statistical Methods
  - There, the label is the state
- However, in this course we will (mostly) stay more general and talk about binary classifiers and one-against-all

(Greedy) classification with IOB

Seminar	at	4	pm	will	be	on	...
O	O	B-stime	I-stime	O	O	O	

- To perform greedy classification, first run your classifier on "Seminar"
- You can use a label feature here like
  -1_Label_StartOfSentence
- Suppose you correctly choose "O"
- Then when classifying "at", use the feature:
  -1_Label_O
- Suppose you correctly choose "O"
- Then when classifying "4", use the feature:
  -1_Label_O
- Suppose you correctly choose "B-stime"
- Then when classifying "pm", use the feature:
  -1_Label_B-stime
- Etc...

Training

- How to create the training data (do feature extraction) should be obvious
  - We can just use the gold standard label of the previous position as our feature

BIEWO Markup

- A popular alternative to IOB markup is BIEWO markup
- E stands for "end"
- W stands for "whole", meaning we have a one-word entity (i.e., this position is both the begin and end)

Seminar	at	4	pm	will	be	on	...
O	O	B-stime	E-stime	O	O	O	

Seminar	at	4	will	be	on	...
O	O	W-stime	O	O	O	

BIEWO vs IOB

- BIEWO fragments the training data
  - Recall that we are learning a binary classifier for each label
  - In our two examples on the previous slide, this means we are not using the same classifiers!
- Use BIEWO when single-word mentions require different features to be active than the first word of a multi-word mention

Conclusion

- I've taught you the basics of:
  - Binary classification using features
    - I also briefly presented word-type embeddings (word2vec) and contextualized word-token embeddings (e.g,. BERT, ELMO)
  - Multiclass classification (using one-against-all)
  - Sequence classification (using a feature that uses the previous decision)
    - And IOB or BIEWO labels
- I've skipped a lot of details
  - I haven't talked about non-greedy ways to do sequence classification
  - And I didn't talk about probabilities, which are used directly, or at least approximated, in many kinds of commonly used linear models!
- Hopefully what I did tell you is fairly intuitive and helps you understand classification, that is the goal

- Further reading:
  - Tom Mitchell. Machine Learning. McGraw Hill 1997 (text book, not free)
- More advanced, highly recommended:
  - Hal Daumé III. A Course in Machine Learning. 2017 (beta version 0.99, free, or 1.0, not free)
- Word embeddings (including word2vec, ELMO, BERT):
  - Noah Smith. Contextual Word Representations: A Contextual Introduction. arXiv 2019 (short article, free)

- Thank you for your attention!