# CSCI 5582
# Artificial Intelligence

Lecture 21
Jim Martin



## Today 11/14

- Review
- Hypothesis Learning
  - Version Spaces
- Break
- Relational Learning
  - ILP

# Review

- Supervised machine learning
  - Naïve Bayes
  - Decision trees
  - Decision lists
  - Ensembles



# Classifiers

- These all provide a way to separate objects into classes based on intrinsic features of the object (encoded as sets of feature/value pairs).
- They don't necessarily provide a definition for the concept learned
- They can't deal with relational data.

# Classifiers

- Uncle?



# Concept Learning

- In concept learning we'd like to learn something akin to a definition: necessary and sufficient conditions for membership in a category
  - Rules out all non-members
  - Includes all members
- And we'd like to be able to deal with relational data
- Assume we're given positive and negative examples of the concept to be learned.

# Data Mining

- The field of data mining is concerned with the extraction of possibly useful rules or patterns from large amounts of data.



# Concept Learning

- And most importantly the concept to be learned is expressed in terms of predicates/propositions that are already known (that is we have a domain theory of some kind).

## Basics

- In the context of concept learning, a hypothesis is just a theory of the concept that
  - Includes all members of the category
  - Excludes all non-members
- A false negative is…
- A false positive is…

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## Concept Learning: Search

- Again its just search. We're searching through the space of possible hypotheses to find one (all?) that do exactly what we want: cover all and only the concepts we're trying to learn.

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## Current Best Hypothesis

Maintain a single hypothesis at a time.

Perform surgery on it on demand.

- If I give it a positive example and it covers it…
- If I give it a negative example and it rejects it…



## Current Best Hypothesis

- If I give a positive example and it rejects it…
  - False negative.
    - Adjust the theory so that
      1. It…
      2. And it…

# Current Best Hypothesis

- If I give it a negative example and it accepts it
  - False positive
    - Adjust the theory so that it
      1. ?
      2. ?

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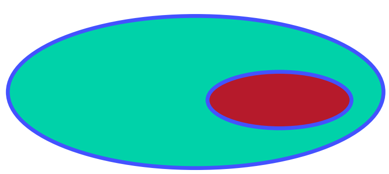
# CBH

- How?
  - Depends on the language being used. But the critical notion to exploit is generalization/specialization



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# CBH

- If you need to cover a falsely rejected positive example…
  - You need to generalize your hypothesis
- If you need to reject a false accepted negative example…
  - You need to specialize your hypothesis



# How…

- Depends on the language… typically
  - Dropping/adding conditions for membership
  - Adding/removing disjuncts from a definition

## So…

- Search is just specializing/generalizing a single hypothesis in response to each successive training example
- Until you cover all and only.
- But….



## But

- The backtracking inherent in CBH is pretty horrible.
- It turns out it isn't really required
- CBH is making commitments early on that it really doesn't have to make
  - Exploit the hierarchy inherent in the logical structure of the hypotheses

## Version Space Learning

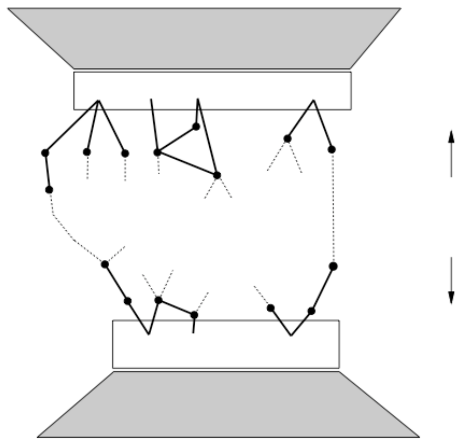
- You can represent the space of hypothesis by representing certain boundaries (without representing the hypotheses) themselves.
- In response to false positives and false negatives you simply adjust the boundaries.
- At the end the space of hypotheses within the boundaries are all consistent with the training data.



## Version Space Learning

- I give you a single positive training example…
  - What's the most general theory you can come up with?
  - What's the most specific theory you can come up with?

# VS



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# Version Space Learning

- Termination….
  - When I run out of training examples
  - When the VS collapses
    - There are no theories left in the space

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## Break

- Look at
  - holmes.txt and tarzan.txt in
  - www.cs.colorado.edu/~martin/Csci5582



## Break

- I'll go over the quiz topics Thursday

# Relational Learning and Inductive Logic Programming

- Fixed feature vectors are a very limited representation of objects.
- Examples or target concept may require relational representation that includes multiple entities with relationships among them.
- First-order predicate logic is a more powerful representation for handling such relational descriptions.



# ILP Example

- Learn definitions of family relationships given data for primitive types and relations.

  brother(A,C), parent(C,B) -> uncle(A,B)

  husband(A,C), sister(C,D), parent(D,B) -> uncle(A,B)
- Given the relevant predicates and a database populated with positive and negative examples
- By database I mean sets of tuples for each of the relevant relations

# FOIL
# First-Order Inductive Logic

- Top-down sequential covering algorithm to learn first order theories.
- Background knowledge provided extensionally (ie. A model)
- Start with the most general rule possible. (T --> P(x))
- Specialize it on demand…
- Specializations of a clause include adding all possible literals one at a time to the antecedent…
  - A -> P
  - B -> P
  - C -> P…

  Where A, B and C are predicates already in the domain theory.

  We're working top-down from the most general hypothesis so what's driving things?



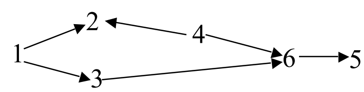
# FOIL

- At a high level.
  - Start with the most general H
  - Repeatedly constructs clauses that cover a subset of the positive examples and none of the negative examples.
  - Then remove the covered positive examples
  - Constructs another clause
  - Repeat until all the positive examples are covered.

# FOIL Training Data

- Background knowledge consists of complete set of tuples for each background predicate for this universe.
- Example: Consider learning a definition for the target predicate `path` for finding a path in a directed acyclic graph.

```
path(X,Y) :- edge(X,Y).
path(X,Y) :- edge(X,Z), path(Z,Y).
```

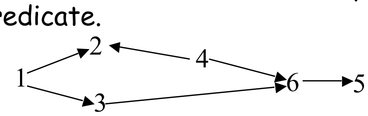



```
edge: {<1,2>,<1,3>,<3,6>,<4,2>,<4,6>,<6,5>}
path: {<1,2>,<1,3>,<1,6>,<1,5>,<3,6>,<3,5>,
       <4,2>,<4,6>,<4,5>,<6,5>}
```



# FOIL Negative Training Data

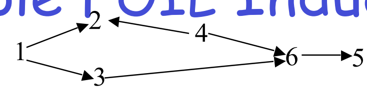
- Negative examples of target predicate can be provided directly, or generated indirectly by making a *closed world assumption*.
  - Every pair of constants <X,Y> not in positive tuples for `path` predicate.




Negative `path` tuples:

```
{<1,1>,<1,4>,<2,1>,<2,2>,<2,3>,<2,4>,<2,5>,<2,6>,
 <3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,<5,1>,
 <5,2>,<5,3>,<5,4>,<5,5>,<5,6>,<6,1>,<6,2>,<6,3>,
 <6,4>,<6,6>}
```

# Sample FOIL Induction




Pos: {<1,2>,<1,3>,<1,6>,<1,5>,<3,6>,<3,5>,
<4,2>,<4,6>,<4,5>,<6,5>}

Neg: {<1,1>,<1,4>,<2,1>,<2,2>,<2,3>,<2,4>,<2,5>,<2,6>,
<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,<5,1>,
<5,2>,<5,3>,<5,4>,<5,5>,<5,6>,<6,1>,<6,2>,<6,3>,
<6,4>,<6,6>}

Start with clause:

`path(X,Y):-.`

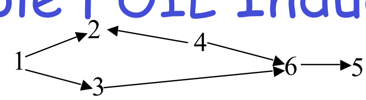
Possible literals to add:

`edge(X,X),edge(Y,Y),edge(X,Y),edge(Y,X),edge(X,Z),`
`edge(Y,Z),edge(Z,X),edge(Z,Y),path(X,X),path(Y,Y),`
`path(X,Y),path(Y,X),path(X,Z),path(Y,Z),path(Z,X),`
`path(Z,Y),X=Y,`

plus negations of all of these.



# Sample FOIL Induction




Pos: {<1,2>,<1,3>,<1,6>,<1,5>,<3,6>,<3,5>,
<4,2>,<4,6>,<4,5>,<6,5>}

Neg: {<1,1>,<1,4>,<2,1>,<2,2>,<2,3>,<2,4>,<2,5>,<2,6>,
<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,<5,1>,
<5,2>,<5,3>,<5,4>,<5,5>,<5,6>,<6,1>,<6,2>,<6,3>,
<6,4>,<6,6>}

Test:

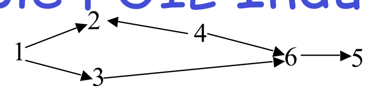
`path(X,Y):- edge(X,X).`

Covers 0 positive examples

Covers 6 negative examples

Not a good literal to try.

# Sample FOIL Induction




Pos: {<1,2>,<1,3>,<1,6>,<1,5>,<3,6>,<3,5>,
<4,2>,<4,6>,<4,5>,<6,5>}

Neg: {<1,1>,<1,4>,<2,1>,<2,2>,<2,3>,<2,4>,<2,5>,<2,6>,
<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,<5,1>,
<5,2>,<5,3>,<5,4>,<5,5>,<5,6>,<6,1>,<6,2>,<6,3>,
<6,4>,<6,6>}

Test:

`path(X,Y):- edge(X,Y).`

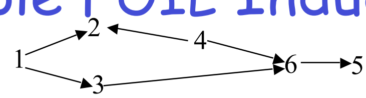
Covers 6 positive examples

Covers 0 negative examples

Chosen as best literal. Result is base clause.



# Sample FOIL Induction




Pos: {<1,6>,<1,5>,<3,5>,
<4,5>}

Neg: {<1,1>,<1,4>,<2,1>,<2,2>,<2,3>,<2,4>,<2,5>,<2,6>,
<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,<5,1>,
<5,2>,<5,3>,<5,4>,<5,5>,<5,6>,<6,1>,<6,2>,<6,3>,
<6,4>,<6,6>}

Test:

`path(X,Y):- edge(X,Y).`

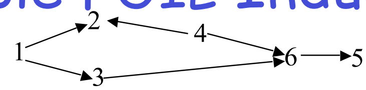
Covers 6 positive examples

Covers 0 negative examples

Chosen as best literal. Result is base clause.

Remove covered positive tuples.

# Sample FOIL Induction




Pos: {<1,6>,<1,5>,<3,5>,
<4,5>}

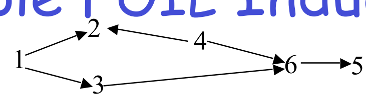
Neg: {<1,1>,<1,4>,<2,1>,<2,2>,<2,3>,<2,4>,<2,5>,<2,6>,
<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,<5,1>,
<5,2>,<5,3>,<5,4>,<5,5>,<5,6>,<6,1>,<6,2>,<6,3>,
<6,4>,<6,6>}

Start new clause

`path(X,Y):-.`



# Sample FOIL Induction




Pos: {<1,6>,<1,5>,<3,5>,
<4,5>}

Neg: {<1,1>,<1,4>,<2,1>,<2,2>,<2,3>,<2,4>,<2,5>,<2,6>,
<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,<5,1>,
<5,2>,<5,3>,<5,4>,<5,5>,<5,6>,<6,1>,<6,2>,<6,3>,
<6,4>,<6,6>}

Test:

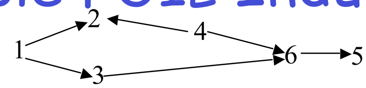
`path(X,Y):- edge(X,Y).`

Covers 0 positive examples

Covers 0 negative examples

Not a good literal.

# Sample FOIL Induction




Pos: {<1,6>,<1,5>,<3,5>,
<4,5>}

Neg: {<1,1>,<1,4>,<2,1>,<2,2>,<2,3>,<2,4>,<2,5>,<2,6>,
<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,<5,1>,
<5,2>,<5,3>,<5,4>,<5,5>,<5,6>,<6,1>,<6,2>,<6,3>,
<6,4>,<6,6>}

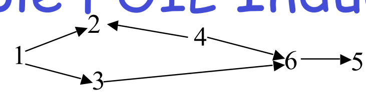
Test:

```
path(X,Y):- edge(X,Z).
```

Covers all 4 positive examples
Covers 14 of 26 negative examples
Eventually chosen as best possible literal



# Sample FOIL Induction




Pos: {<1,6>,<1,5>,<3,5>,
<4,5>}

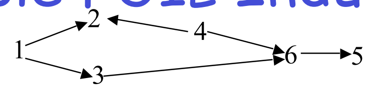
Neg: {<1,1>,<1,4>,
<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,
<6,1>,<6,2>,<6,3>,
<6,4>,<6,6>}

Test:

```
path(X,Y):- edge(X,Z).
```

Covers all 4 positive examples
Covers 15 of 26 negative examples
Eventually chosen as best possible literal
Negatives still covered, remove uncovered examples.

# Sample FOIL Induction




Pos: `{<1,6,2>,<1,6,3>,<1,5>,<3,5>,`
`<4,5>}`

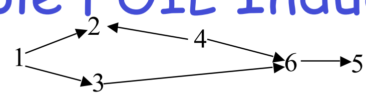
Neg: `{<1,1>,<1,4>,`
`<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,`
`<6,1>,<6,2>,<6,3>,`
`<6,4>,<6,6>}`

Test:
`path(X,Y):- edge(X,Z).`

Covers all 4 positive examples
Covers 15 of 26 negative examples
Eventually chosen as best possible literal
Negatives still covered, remove uncovered examples.
Expand tuples to account for possible `Z` values.



# Sample FOIL Induction



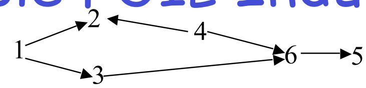

Pos: `{<1,6,2>,<1,6,3>,<1,5,2>,<1,5,3>,<3,5>,`
`<4,5>}`

Neg: `{<1,1>,<1,4>,`
`<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,`
`<6,1>,<6,2>,<6,3>,`
`<6,4>,<6,6>}`

Test:
`path(X,Y):- edge(X,Z).`

Covers all 4 positive examples
Covers 15 of 26 negative examples
Eventually chosen as best possible literal
Negatives still covered, remove uncovered examples.
Expand tuples to account for possible `Z` values.

# Sample FOIL Induction




Pos: `{<1,6,2>,<1,6,3>,<1,5,2>,<1,5,3>,<3,5,6>,`
`<4,5>}`

Neg: `{<1,1>,<1,4>,`
`<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,`
`<6,1>,<6,2>,<6,3>,`
`<6,4>,<6,6>}`

Test:

```
path(X,Y):- edge(X,Z).
```

Covers all 4 positive examples

Covers 15 of 26 negative examples

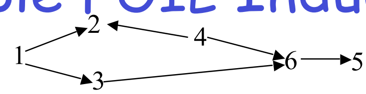
Eventually chosen as best possible literal

Negatives still covered, remove uncovered examples.

Expand tuples to account for possible `Z` values.



# Sample FOIL Induction




Pos: `{<1,6,2>,<1,6,3>,<1,5,2>,<1,5,3>,<3,5,6>,`
`<4,5,6>}`

Neg: `{<1,1>,<1,4>,`
`<3,1>,<3,2>,<3,3>,<3,4>,<4,1>,<4,3>,<4,4>,`
`<6,1>,<6,2>,<6,3>,`
`<6,4>,<6,6>}`

Test:

```
path(X,Y):- edge(X,Z).
```

Covers all 4 positive examples

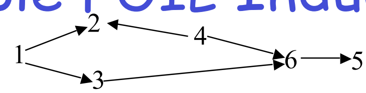
Covers 15 of 26 negative examples

Eventually chosen as best possible literal

Negatives still covered, remove uncovered examples.

Expand tuples to account for possible `Z` values.

# Sample FOIL Induction




Pos: {<1,6,2>,<1,6,3>,<1,5,2>,<1,5,3>,<3,5,6>,
<4,5,6>}

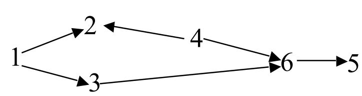
Neg: {<1,1,2>,<1,1,3>,<1,4,2>,<1,4,3>,<3,1,6>,<3,2,6>,
<3,3,6>,<3,4,6>,<4,1,2>,<4,1,6>,<4,3,2>,<4,3,6>
<4,4,2>,<4,4,6>,<6,1,5>,<6,2,5>,<6,3,5>,
<6,4,5>,<6,6,5>}

Test:
`path(X,Y):- edge(X,Z).`

Covers all 4 positive examples
Covers 15 of 26 negative examples
Eventually chosen as best possible literal
Negatives still covered, remove uncovered examples.
Expand tuples to account for possible `Z` values.



# Sample FOIL Induction

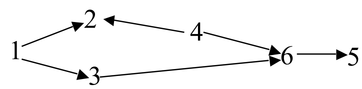



Pos: {<1,6,2>,<1,6,3>,<1,5,2>,<1,5,3>,<3,5,6>,
<4,5,6>}

Neg: {<1,1,2>,<1,1,3>,<1,4,2>,<1,4,3>,<3,1,6>,<3,2,6>,
<3,3,6>,<3,4,6>,<4,1,2>,<4,1,6>,<4,3,2>,<4,3,6>
<4,4,2>,<4,4,6>,<6,1,5>,<6,2,5>,<6,3,5>,
<6,4,5>,<6,6,5>}

Continue specializing clause:
`path(X,Y):- edge(X,Z).`

# Sample FOIL Induction




Pos: {<1,6,2>,<1,6,3>,<1,5,2>,<1,5,3>,<3,5,6>,
<4,5,6>}

Neg: {<1,1,2>,<1,1,3>,<1,4,2>,<1,4,3>,<3,1,6>,<3,2,6>,
<3,3,6>,<3,4,6>,<4,1,2>,<4,1,6>,<4,3,2>,<4,3,6>
<4,4,2>,<4,4,6>,<6,1,5>,<6,2,5>,<6,3,5>,
<6,4,5>,<6,6,5>}

Test:

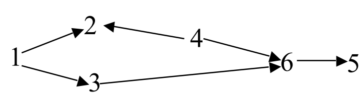
```
path(X,Y):- edge(X,Z),edge(Z,Y).
```

Covers 3 positive examples

Covers 0 negative examples



# Sample FOIL Induction




Pos: {<1,6,2>,<1,6,3>,<1,5,2>,<1,5,3>,<3,5,6>,
<4,5,6>}

Neg: {<1,1,2>,<1,1,3>,<1,4,2>,<1,4,3>,<3,1,6>,<3,2,6>,
<3,3,6>,<3,4,6>,<4,1,2>,<4,1,6>,<4,3,2>,<4,3,6>
<4,4,2>,<4,4,6>,<6,1,5>,<6,2,5>,<6,3,5>,
<6,4,5>,<6,6,5>}

Test:

```
path(X,Y):- edge(X,Z),path(Z,Y).
```

Covers 4 positive examples     Covers 0 negative examples

Eventually chosen as best literal; completes clause.

Definition complete, since all original <X,Y> tuples are covered (by way of covering some <X,Y,Z> tuple.)

## More Realistic Applications

- Classifying chemical compounds as mutagenic (cancer causing) based on their graphical molecular structure and chemical background knowledge.
- Classifying web documents based on both the content of the page and its links to and from other pages with particular content.
  - A web page is a university faculty home page if:
    - It contains the words "Professor" and "University", and
    - It is pointed to by a page with the word "faculty", and
    - It points to a page with the words "course" and "exam"



## Rule Learning and ILP Summary

- There are effective methods for learning symbolic rules from data using greedy sequential covering and top-down or bottom-up search.
- These methods have been extended to first-order logic to learn relational rules and recursive Prolog programs.
- Knowledge represented by rules is generally more interpretable by people, allowing human insight into what is learned and possible human approval and correction of learned knowledge.