

# DSCI 573: Model Selection and Feature Selection

Structure Learning

Winter 2018

# Structure Learning: Unsupervised Feature Selection

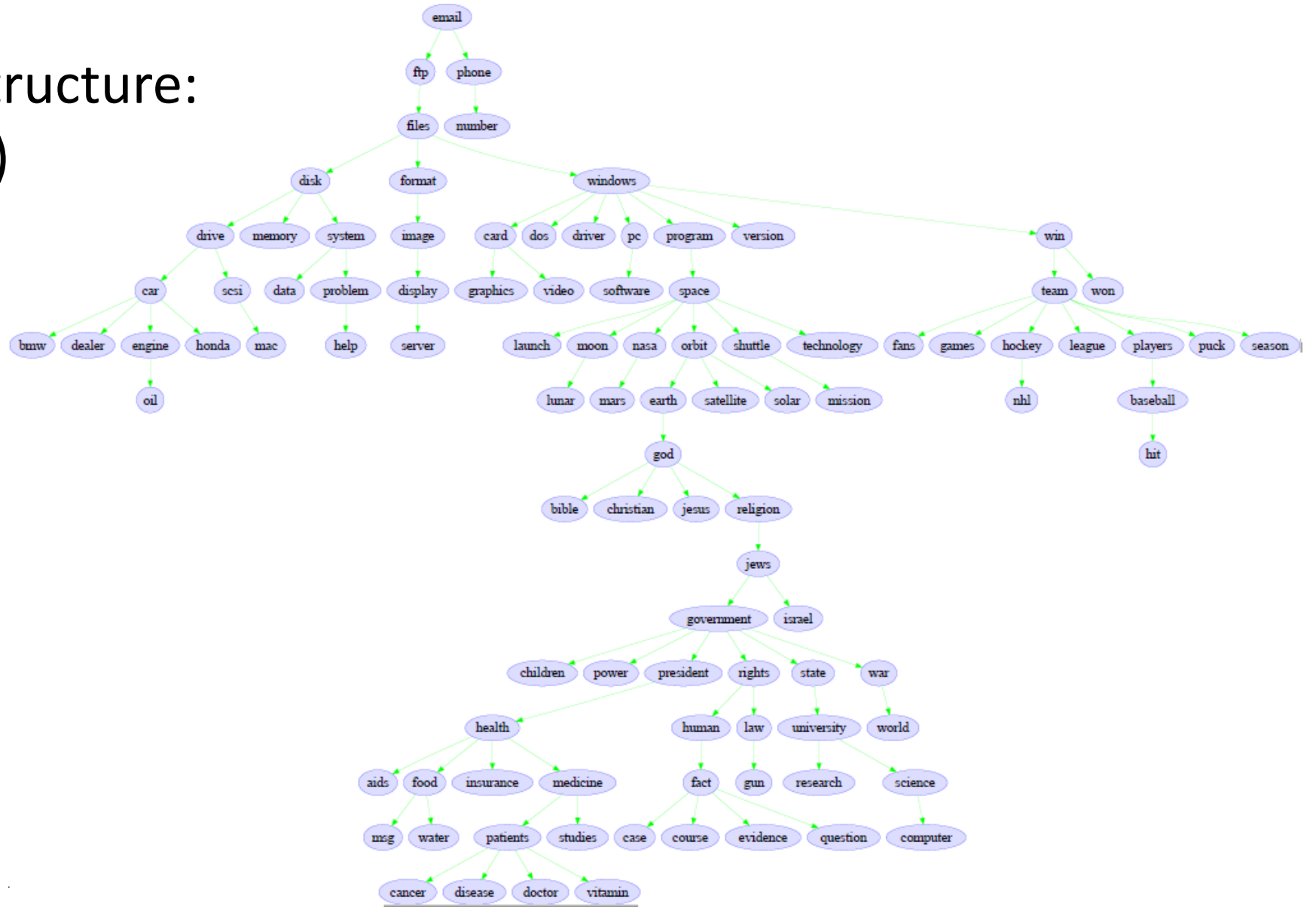
- “News” data: presence of 100 words in 16k newsgroup posts:

car	drive	files	hockey	mac	league	pc	win
0	0	1	0	1	0	1	0
0	0	0	1	0	1	0	1
1	1	0	0	0	0	0	0
0	1	1	0	1	0	0	0
0	0	1	0	0	0	1	1

- Which words are related to each other?
- Problem of **structure learning**: **unsupervised feature selection**.

# Structure Learning: Unsupervised Feature Selection

- Optimal tree structure:  
(ignore arrows)



# Naïve Approach: Association Networks

- A naïve approach to structure learning (“association networks”):
  - For each pair of variables, compute a measure of similarity or dependence.
- Using these  $n^2$  similarity values either:
  - Select all pairs whose similarity is above a threshold.
  - Select the “top  $k$ ” most similar features to each feature ‘ $j$ ’.
- Main problems:
  - Usually, most variables are dependent (too many edges).
    - “Sick” is getting connected to “Tuesdays” even if “tacos” are a variable.
  - “True” neighbours may not have the highest dependence.
    - “Sick” might get connected to “Tuesdays” before it gets connected to “milk”.
- (Variation: best tree can be found as minimum spanning tree problem.)

# Example: Vancouver Rain Data

- Consider modeling the “Vancouver rain” dataset.

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	...
Month 1	0	0	0	1	1	0	0	1	1	
Month 2	1	0	0	0	0	0	1	0	0	
Month 3	1	1	1	1	1	1	1	1	1	
Month 4	1	1	1	1	0	0	1	1	1	
Month 5	0	0	0	0	1	1	0	0	0	
Month 6	0	1	1	0	0	0	0	1	1	

- The strongest signal in the data is the simple relationship:
  - If it rained yesterday, it’s likely to rain today (> 50% chance that  $x^{t-1} = x^t$ ).
  - But an “association network” might connect all days (all dependent).

# Dependency Networks

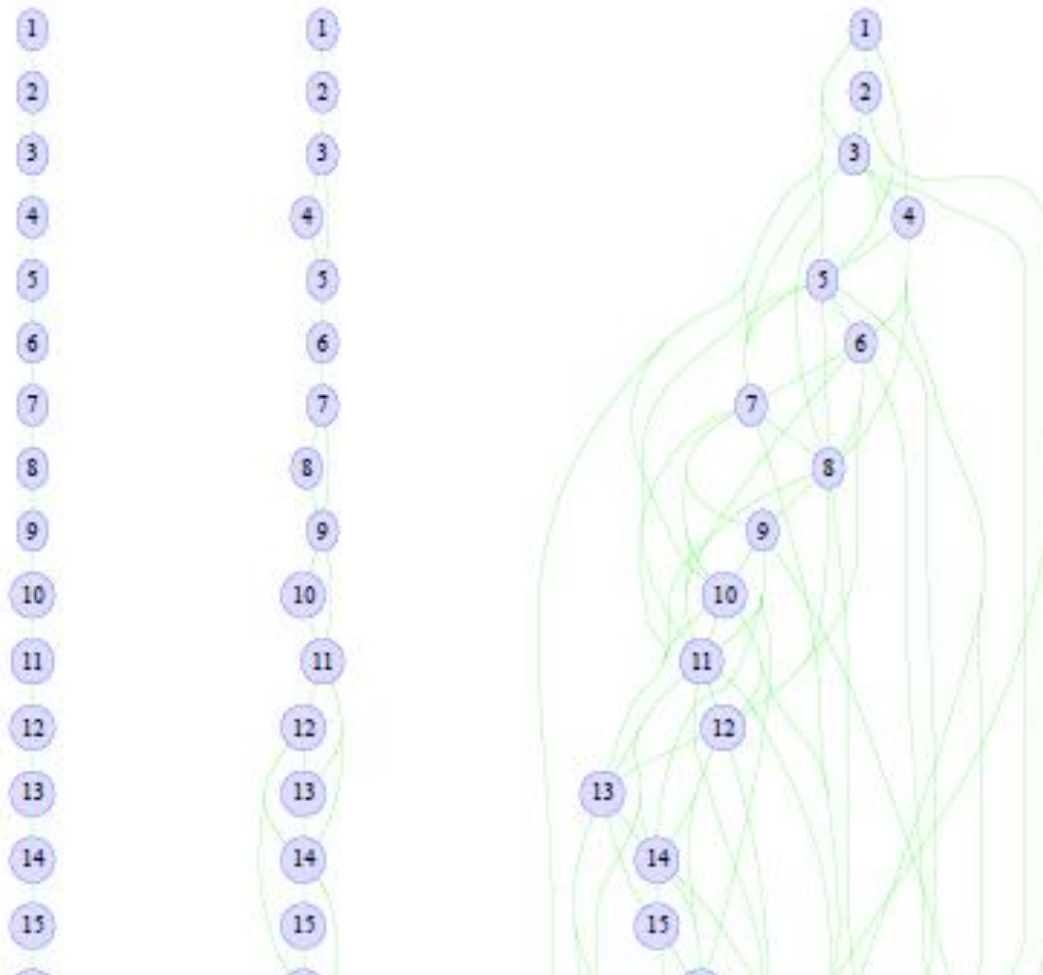
- A better approach is **dependency networks**:
  - For each variable 'j', **make it the target in a supervised learning problem.**

$$X = \begin{bmatrix} | & | & | & | & | \\ x^1 & x^2 & x^3 & x^4 & x^5 \\ | & | & | & | & | \end{bmatrix} \Rightarrow \bar{X} = \begin{bmatrix} | & | & | & | \\ x^1 & x^2 & x^3 & x^5 \\ | & | & | & | \end{bmatrix} \quad y = \begin{bmatrix} | \\ x^4 \\ | \end{bmatrix}$$

- Now we can **use any feature selection method** to choose j's "neighbours".
  - Forward selection, L1-regularization, ensemble methods, etc.
- Can capture **conditional independence**:
  - Might connect "sick" to "tacos", and "tacos" to "Tuesdays" (w/o sick-tacos).

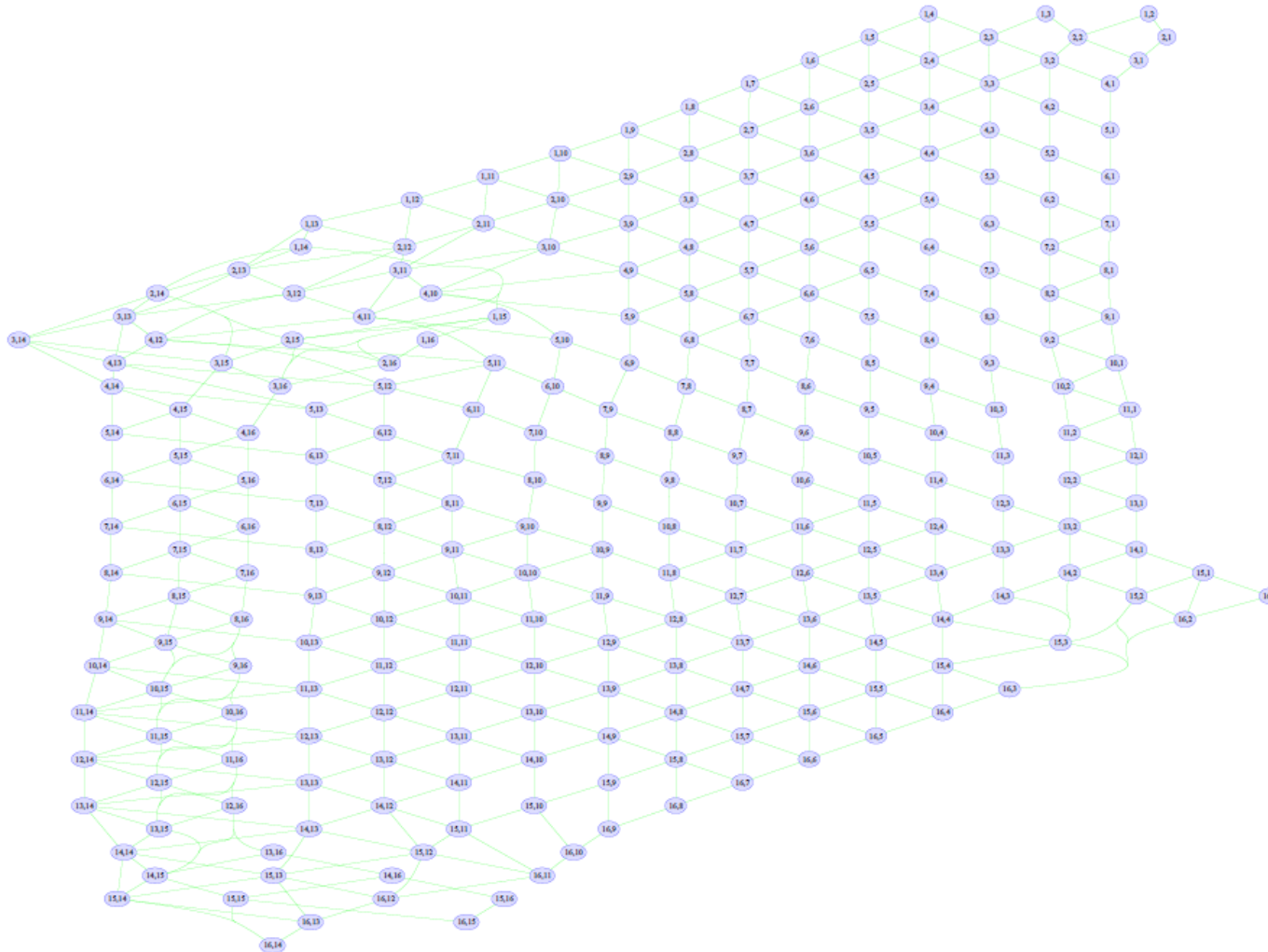
# Dependency Networks

- Dependency network fit to Vancouver rain data (different  $\lambda$  values):



# Dependency Networks

- Variation on dependency networks on digit image pixels:



Another popular structure learning method is the "PC" algorithm.



# Summary

- **Structure learning** is “unsupervised” feature selection.
- **Association networks** make graph by finding similar features.
- **Dependency networks** use feature selection with feature ‘j’ as ‘y’.