

Data X

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HW04 - Decision Trees, Entropy, NLP, SQL

Part 1

Part 1.1

FINAL RESULTS:

Entropy Values:

Above 30: 1.0 HasJob: 0.951205059305 HasFam: 0.811278124459

Information Gained:

Above 30: 0.0 HasJob: 0.0487949406954 HasFam: 0.188721875541

CALCULATIONS:

Weights of each X feature

$$w_{\text{above30}} = 0.5$$

$$w_{\text{hasJob}} = 0.625$$

$$w_{\text{hasFam}} = 0.75$$

Probabilities of defaulting given each X feature is positive or negative.

$$p_{\text{above30}} = P(\text{default}|\text{above30}) = 0.5$$

$$p_{\text{above30}} = P(\text{default}|\neg\text{above30}) = 0.5$$

$$p_{\text{hasJob}} = P(\text{default}|\text{hasJob}) = 0.4$$

$$p_{\text{hasJob}} = P(\text{default}|\neg\text{hasJob}) = 0.67$$

$$p_{\text{hasFam}} = P(\text{default}|\text{hasFam}) = 0.25$$

$$p_{\text{hasFam}} = P(\text{default}|\neg\text{hasFam}) = 0.75$$

Entropy Calculations

$$H(x) = \sum_x p(x) \log\left(\frac{1}{p(x)}\right)$$

```
p_above30_ent = (p_above30*np.log2(1/p_above30) +  
(1-p_above30)*np.log2(1/(1-p_above30))) * w_above30 +  
(p_notAbove30*np.log2(1/p_notAbove30) +  
(1-p_notAbove30)*np.log2(1/(1-p_notAbove30))) * (1-w_above30)
```

```
p_above30_ent = 1.0
```

```
p_hasJob_ent = (p_hasJob*np.log2(1/p_hasJob) + (1-p_hasJob)*np.log2(1/(1-p_hasJob))) *  
w_hasJob + (p_notHasJob*np.log2(1/p_notHasJob) +  
(1-p_notHasJob)*np.log2(1/(1-p_notHasJob))) * (1-w_hasJob)
```

```
p_hasJob_ent = 0.951205059305
```

```
p_hasFam_ent = (p_hasFam*np.log2(1/p_hasFam) + (1-p_hasFam)*np.log2(1/(1-p_hasFam))) *  
w_hasFam + (p_notHasFam*np.log2(1/p_notHasFam) +  
(1-p_notHasFam)*np.log2(1/(1-p_notHasFam))) * (1-w_hasFam)
```

```
p_hasFam_ent = 0.811278124459
```

Part 1.2

```
A = 0.7
```

```
B = 0.2
```

```
C = 0.1
```

```
S_ent = A*np.log2(1/A) + B*np.log2(1/B) + C*np.log2(1/C) = 1.1568
```

S has an entropy of 1.1568, meaning it should not be compressed into any number of bits less than that as it will be at risk of losing information.

Part 2

Part 2.a - Preprocessing & Modelling

For preprocessing the following steps were used:

1. The body of text was read as a csv using pandas into a dataframe with a sentence per row
2. Manually tokenized:

We can also see how close certain words are to each other, there is a clear cluster around (-0.5, 0). However, we can also see that there are certain words that are further away from the

cluster and are quite topical to the text - i.e. “young”, “mrs”, and “lady” in the upper right quadrant. I believe this can be considered as another cluster and these are topically related. However, based on the PCA, the distance between these words are relatively far. This is not a great measure for how correlated words are.

Part 2.d - 5 Intrinsic Evaluations

Model Similarity - “elizabeth” & “girl”: 0.994126302661

Most Similar - “girl”: ('even', 0.9997328519821167)

Doesn't Match - 'story', 'great', 'spirit', 'disposition', 'delighted', 'altogether': spirit

Most Similar - “woman”: ('great', 0.9997955560684204)

Model Similarity - “great”, “spirit”: 0.996579198264

Part 3

3.1.1. SELECT all records in the table.

'SELECT * FROM parents'

	parent	child
0	abraham	barack
1	abraham	clinton
2	delano	herbert
3	eisenhower	fillmore
4	fillmore	abraham
5	fillmore	delano
6	fillmore	grover

3.1.2. SELECT child and parent, where abraham is the parent.

'SELECT * FROM parents WHERE parent="abraham"'

	parent	child
0	abraham	barack
1	abraham	clinton

3.1.3. SELECT all children that have an 'e' in their name (hint: use LIKE and '%e%').

'SELECT * FROM parents WHERE child LIKE "%e%"'

	parent	child
--	--------	-------

0	delano	herbert
1	eisenhower	fillmore
2	fillmore	delano
3	fillmore	grover

3.1.4. SELECT all unique parents (use SELECT DISTINCT) and order them by name, descending order (i.e. fillmore first)

'SELECT DISTINCT parent FROM parents ORDER BY parent DESC'

	parent
0	fillmore
1	eisenhower
2	delano
3	abraham

3.1.5. SELECT all dogs that are siblings (one-to-one relations). Only show a sibling pair once. To do this you need to select two times from the parents table

```

-----
SELECT parent, COUNT(*)
FROM parents
GROUP BY parent
HAVING COUNT(*) > 1
-----

```

```

-----
SELECT child
FROM parents
WHERE parent="abraham"
OR
parent = "fillmore"
-----

```

	child
0	barack
1	clinton
2	abraham

3	delano
4	grover

3.2.1. COUNT the number of short haired dogs

```
'SELECT *, COUNT(fur) FROM dogs WHERE fur="short"'
```

	name	fur	COUNT(fur)
0	grover	short	3

3.2.2. JOIN tables parents and dogs and SELECT the parents of curly dogs.

```

-----
SELECT parent
FROM dogs
INNER JOIN parents ON dogs.name = parents.child
WHERE fur="curly";
-----

```

	parent
0	eisenhower
1	delano

3.2.3. JOIN tables parents and dogs, and SELECT the parents and children that have the same fur type. Only show them once.

```

-----
SELECT parent, child
FROM parents
LEFT JOIN dogs ON parents.parent == dogs.name
LEFT JOIN dogs AS dogs2 ON parents.child == dogs2.name
WHERE dogs.fur==dogs2.fur
-----

```

	parent	child
0	abraham	clinton

3.3.1. SELECT the animal with the minimum weight. Display kind and min_weight.

```
SELECT *, MIN(weight) FROM animals
```

	kind	legs	weight	MIN(weight)
0	parrot	2	6	6

3.3.2. Use the aggregate function AVG to display a table with the average number of legs and the average weight.

```
SELECT AVG(legs), AVG(weight) FROM animals
```

	AVG(legs)	AVG(weight)
0	3.0	2009.333333

3.3.3. SELECT the animal kind(s) that have more than two legs, but weighs less than 20. Display kind, weight, legs.

```
SELECT * FROM animals  
WHERE legs > 2 AND weight < 20
```

	kind	legs	weight
0	cat	4	10
1	ferret	4	10

3.3.4. SELECT the average weight for all the animals with 2 legs and the animals with 4 legs (by using GROUP BY).

```
SELECT AVG(weight), legs FROM animals  
GROUP BY legs
```

	AVG(weight)	legs
0	4005.333333	2
1	13.333333	4

