

# Factor Graphs And Unsupervised Joke Generation

Alex Bolton

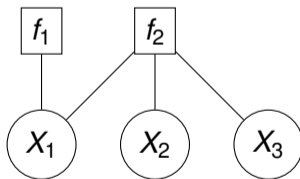
MathsJam Gathering 2019

# Factor Graph

## Definition

A factor graph is a graph that represents the factorisation of a function.

E.g. let  $g(X_1, X_2, X_3) = X_1(X_1 + X_2 + X_3) = f_1(X_1)f_2(X_1, X_2, X_3)$ :  
Its factor graph is



# Factor Graphs In Probability

Factor graphs can represent the factorisation of probabilities.

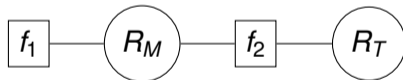
- E.g. joint probability of rain on Monday and on Tuesday ( $R_M$  and  $R_T$ ).

$$P(R_M, R_T) = P(R_M)P(R_T | R_M)$$

or

$$P(R_M, R_T) = f_1(R_M)f_2(R_M, R_T)$$

So the factor graph looks like



Factor  $f_1$  determines whether it rains on Monday, and factor  $f_2$  determines if it rains on Tuesday given whether it rained on Monday.

# Unsupervised Joke Generation

“Unsupervised Joke Generation From Big Data” (Petrović and Matthews) uses factor graphs to generate jokes of the form

I like my  $X$  like I like my  $Y$ :  $Z$ .

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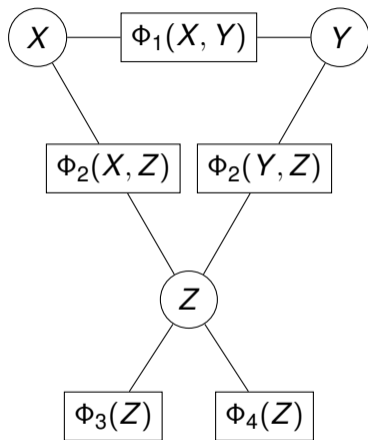
- I like my women like I like my tea: hot
- I like my man like I like my homework: marked.

The probability that a joke of the form

I like my  $X$  like I like my  $Y$ :  $Z$ .

is funny is a function  $p(X, Y, Z)$ .

# Unsupervised Joke Generation Factor Graph



The model presented as a factor graph.

First factor encodes that dissimilar nouns lead to funnier jokes:

$$\Phi_1(x, y) = 1 / \textit{similarity}(x, y)$$

Without this assumption we get anti-jokes:

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$$\Phi_1(x, y) = 1 / \textit{similarity}(x, y)$$

Without this assumption we get anti-jokes:

I like my tea like I like my coffee: hot.

Second factor encodes that the joke is funnier if  $Z$  is often used to describe  $X$ :

$$\Phi_2(x, z) = \textit{co-occurrence}(x, z)$$

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I like my teapot like I like my fireplace:

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Without this assumption we get anti-jokes:

I like my teapot like I like my fireplace: crazy.

Third factor encodes that the joke is funnier if  $Z$  is not a common adjective:

$$\Phi_3(z) = 1 / \text{frequency}(z)$$

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I like my dogs like I like my quality of life:

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$$\Phi_3(z) = 1 / \text{frequency}(z)$$

Without this assumption we get anti-jokes:

I like my dogs like I like my quality of life: good.

Final factor encodes that the joke is funnier if  $Z$  has many different senses, because the humour often comes from  $Z$  being used on one sense for  $X$  and another for  $Y$ :

$$\Phi_4(z) = \text{senses}(z)$$

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Without this assumption we get anti-jokes:

I like my horror films like I like my murder: gruesome.

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- 16% of the jokes were found funny!

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I like my coffee like I like my war:

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I like my coffee like I like my war: cold.

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I like my coffee like I like my war: cold.  
I like my relationships like I like my source:

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Two of the jokes:

I like my coffee like I like my war: cold.  
I like my relationships like I like my source: open.

- Factor graphs can represent probabilities.
- They can also be used to help generate jokes!