10. Topic Models II: Beyond LDA

DS-GA 1015, Text as Data
Arthur Spirling

April 20, 2021

Last time...

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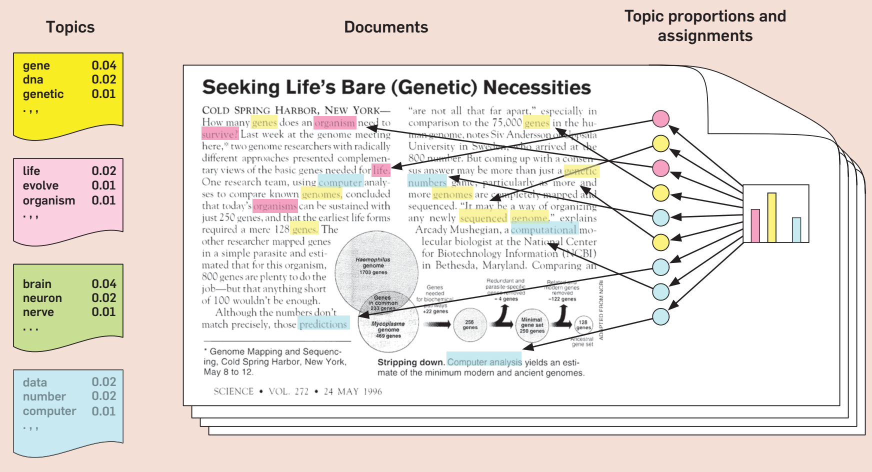

Topics
Documents
Topic proportions and assignments
gene 0.04
dna 0.02
genetic 0.01
. , ,
life 0.02
evolve 0.01
organism 0.01
. , ,
brain 0.04
neuron 0.02
nerve 0.01
. . .
data 0.02
number 0.02
computer 0.01
. , ,
Seeking Life's Bare (Genetic) Necessities
* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.
Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.
SCIENCE • VOL. 272 • 24 MAY 1996

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But topic prevalence and topic content are $f(X)$ [STM]

Lots of other ideas!

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hierarchical LDA, pachinko allocation, nonparametric pachinko allocation,factorial LDA, gamma-poisson factorization, shared component topic models, dirichlet multinomial regression topic models, nested hierarchical dirichlet process topic model, focused topic model, inverse regression topic model, ideal point topic model, discrete infinite logistic normal topic model multilingual topic model, markov topic model, relational topic model, syntactic topic model, supervised latent dirichlet allocation

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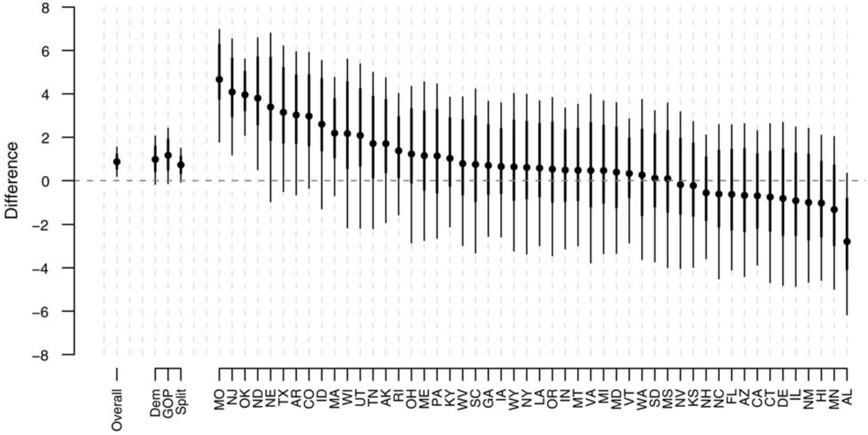

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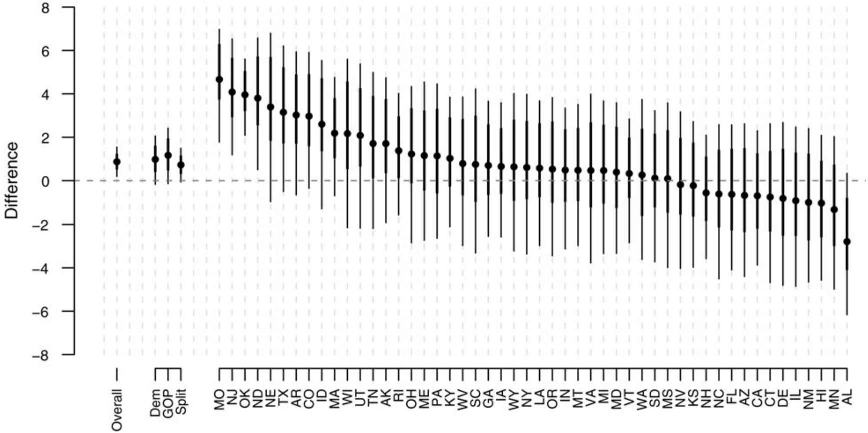

Senators from same states talk about more similar things than Senators from different states (generally).

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Shows improved model fit over LDA. BTW, note that STM (below) reduces to CTM if no covariates are specified.

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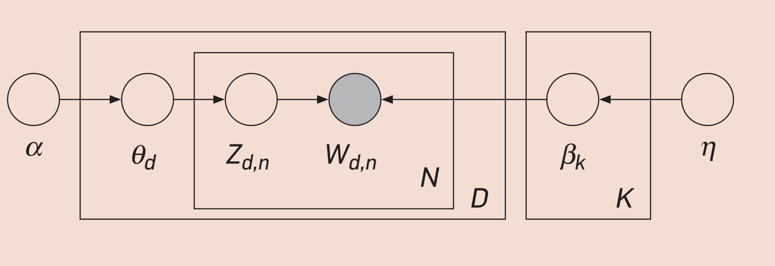
Recall LDA. . .



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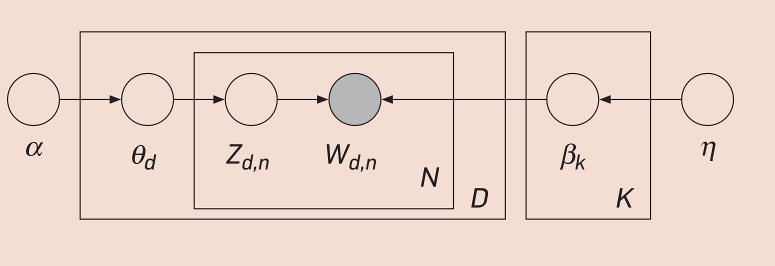

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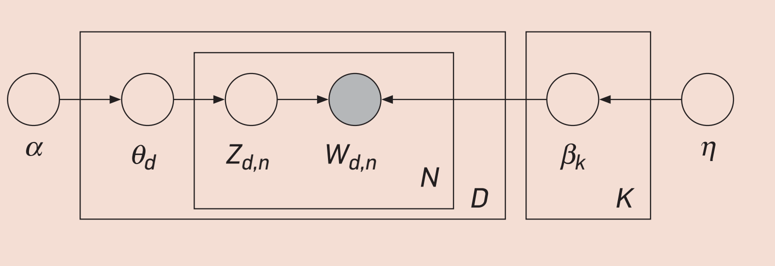

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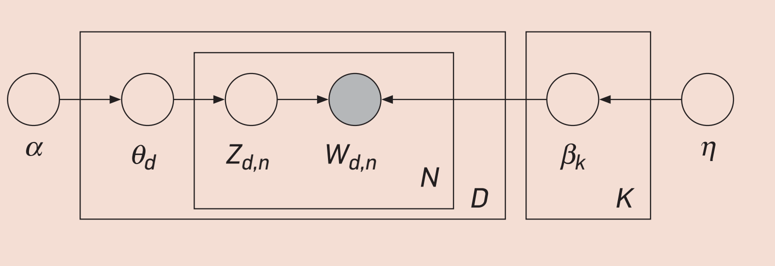

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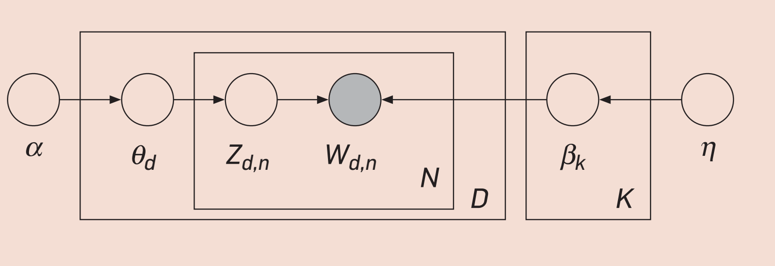

. . . there are multiple documents, but we don't care about their order. Our results are the 'same' regardless of how we reorder the documents and feed them to the model.

Dynamic Topic Model has a different model for each time period, with topics allowed to evolve over time. . .

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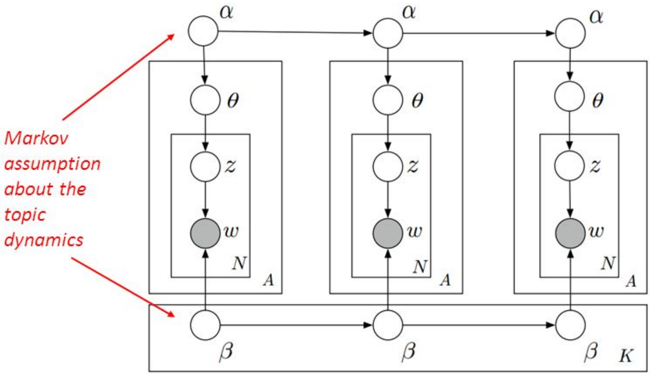

Markov assumption about the topic dynamics
α
α
α
θ
θ
θ
z
z
z
w
w
w
N
N
N
A
A
A
β
β
β
K

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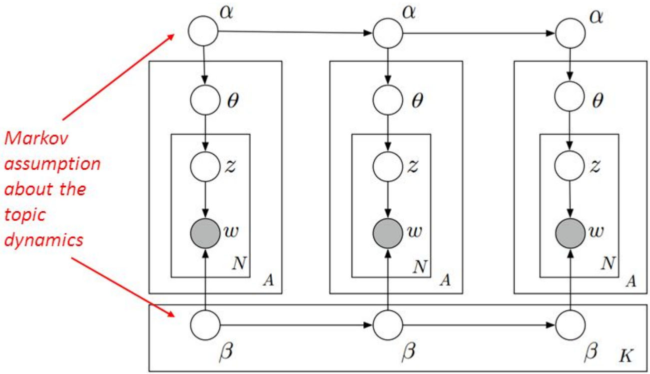

Now, mean parameters for the topic proportions (αs) and what's in the topics (in terms of words, βs) are connected over time via a simple evolutionary process (West & Harrison, 1997).

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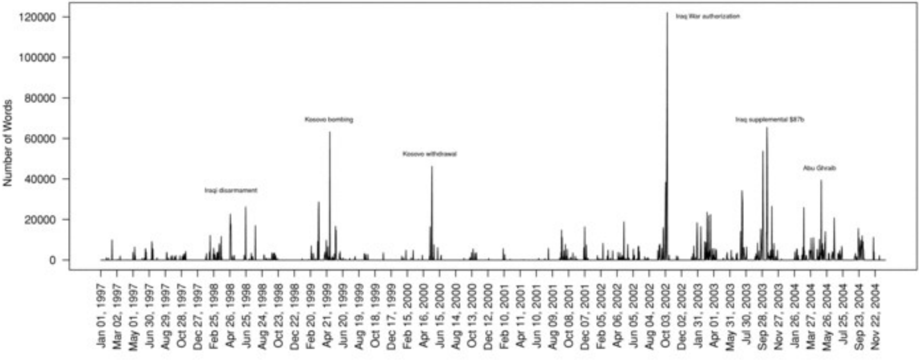
BTW, paper has a lot of validation!

Attention to Defense [Use of Force]



(b) *The Number of Words on the 'Defense [Use of Force]' Topic Per Day*

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Including covariates allows for (a) more accurate estimation and (b) better interpretatability.

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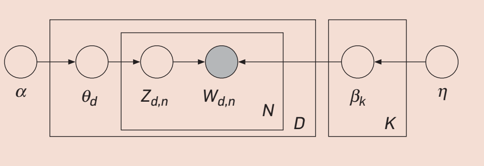

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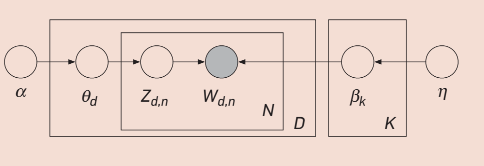

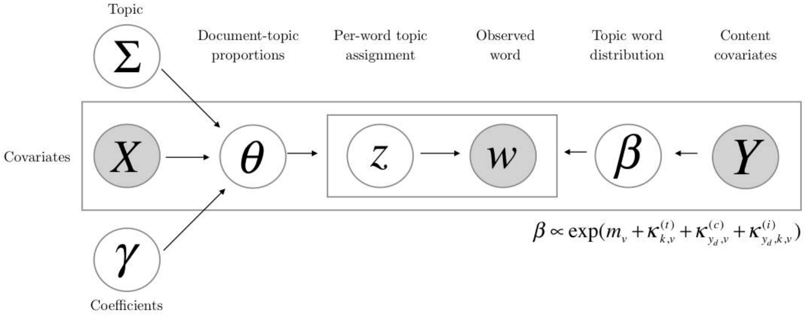

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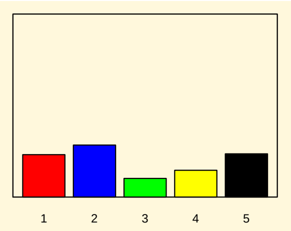

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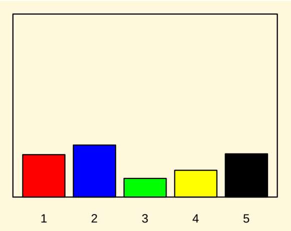

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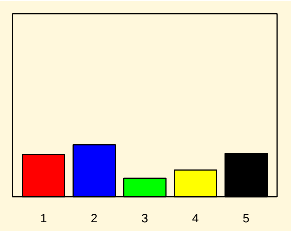

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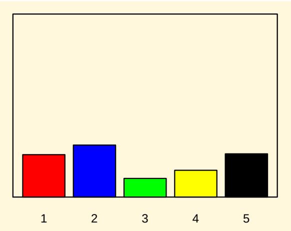

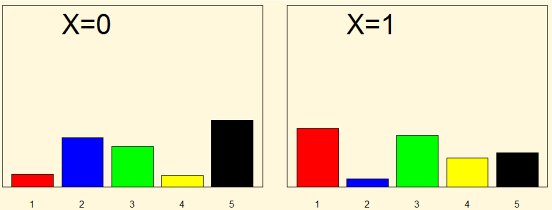

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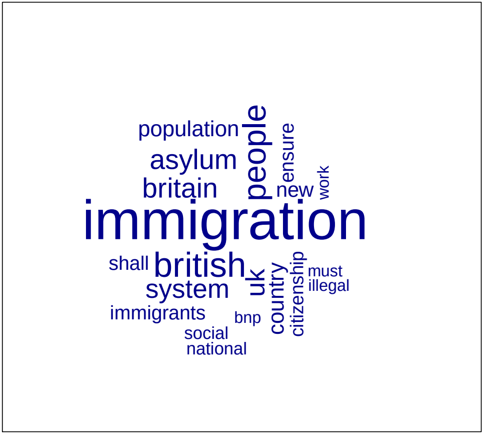

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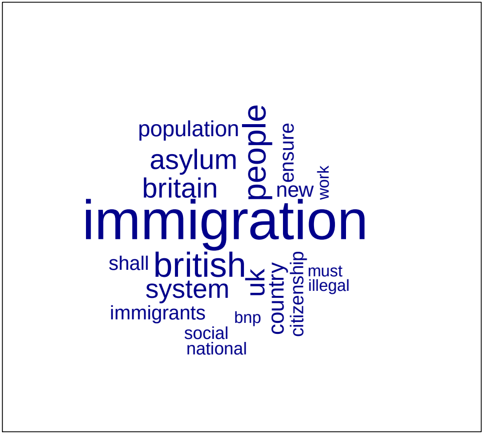

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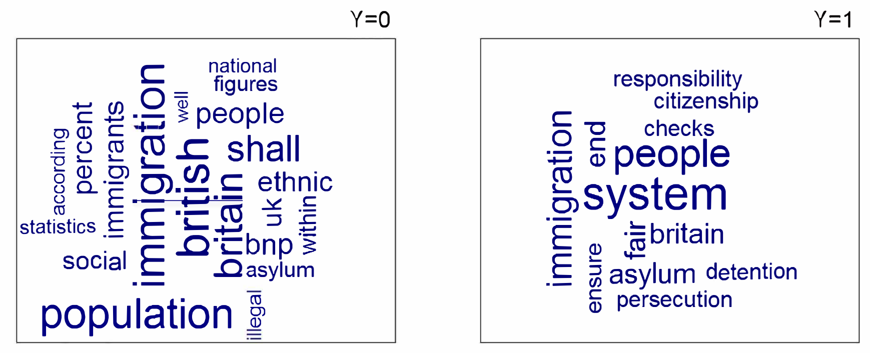

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We can systematically learn about analogies and similarities.

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e.g. Word2Vec: a powerful way to create the word vectors. Comes in two types/models, Continuous Bag of Words (CBOW) and Skip-Gram.

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Continuous Bag of Words (CBOW): A Primer

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Well. . .

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Well...

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And for ‘`over`’...

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Until `lazy` → `dog`, and ending with `lazy` ← `dog` (because we have no other context for this one)

The data

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Input	Output	Ob #	the	quick	brown	fox	jumped	over	the	lazy	dog

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the	quick	1	1	0	0	0	0	0	0	0	0
quick	the	2	0	1	0	0	0	0	0	0	0

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quick	brown	3	0	1	0	0	0	0	0	0	0

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quick	the	2	0	1	0	0	0	0	0	0	0
quick	brown	3	0	1	0	0	0	0	0	0	0
brown	quick	4	0	0	1	0	0	0	0	0	0
brown	fox	5	0	0	1	0	0	0	0	0	0
fox	brown	6	0	0	0	1	0	0	0	0	0
fox	jumped	7	0	0	0	1	0	0	0	0	0
jumped	fox	8	0	0	0	0	1	0	0	0	0
jumped	over	9	0	0	0	0	1	0	0	0	0
over	jumped	10	0	0	0	0	0	1	0	0	0
over	the	11	0	0	0	0	0	1	0	0	0
the	over	12	0	0	0	0	0	0	1	0	0
the	lazy	13	0	0	0	0	0	0	1	0	0
lazy	the	14	0	0	0	0	0	0	0	1	0
lazy	dog	15	0	0	0	0	0	0	0	1	0
dog	lazy	16	0	0	0	0	0	0	0	0	1

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jumped	over	9	0	0	0	0	1	0	0	0	0
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over	the	11	0	0	0	0	0	1	0	0	0
the	over	12	0	0	0	0	0	0	1	0	0
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‘one-hot encoding’

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In practice, neural nets used for the most common models are very simple linear ones, but it doesn't hurt to give a (hand-waving) overview...

Neural Nets: A Primer

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(b) interpretation—understanding what the models says about the DGP is difficult.

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To keep things simple, let's suppose that we have two Xs and that there will be one function g...

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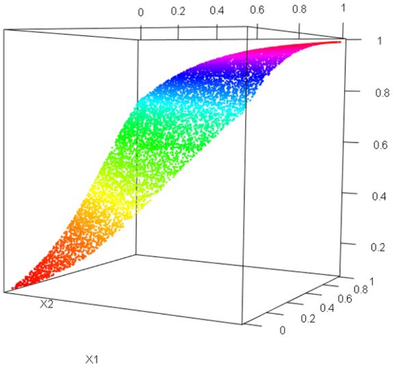

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Turns out that this idea—non-linear functions of linear combinations of Xs—allows essentially infinite flexibility: we can approximate anything we like (some smoothness restrictions in practice).

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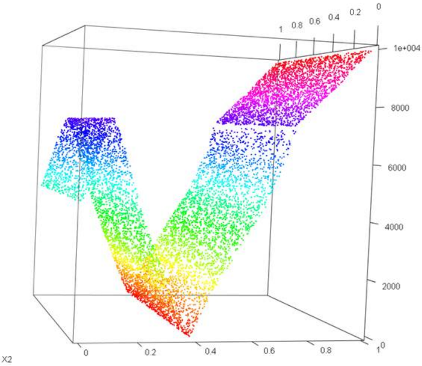

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Transform those outputs into something useful for a class prediction problem, like the multinomial logit transform (called 'softmax' in this literature):

$$g_k(T_k) = \frac{\exp(T_k)}{\sum_{t=1}^{K} \exp(T_k)}$$

Schematic

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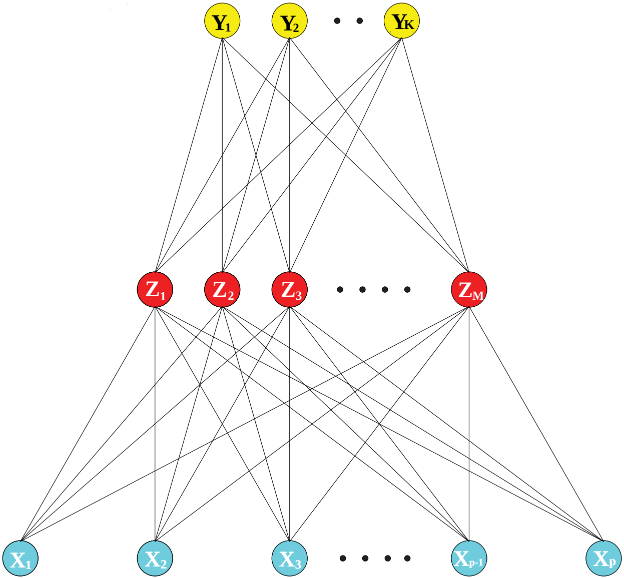
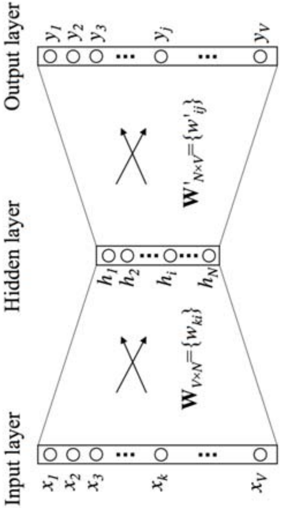


Back to Embeddings (CBOW)

Schematic of CBOW



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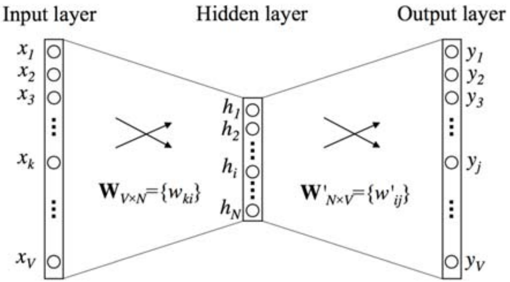

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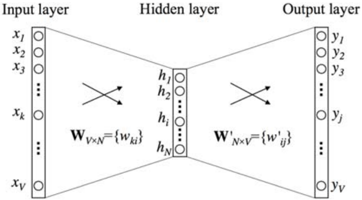

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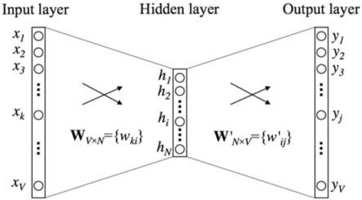

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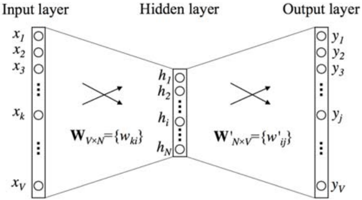

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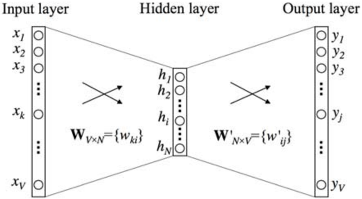

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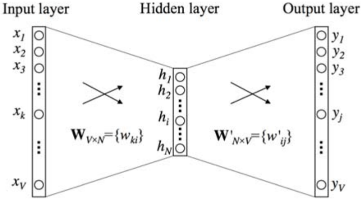

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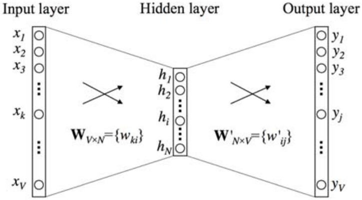

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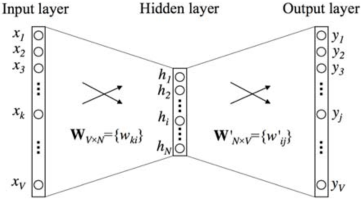

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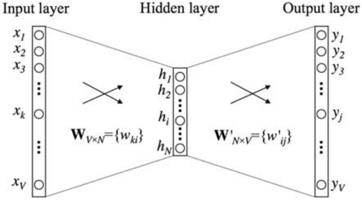

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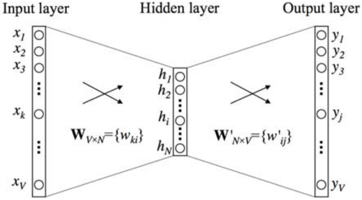

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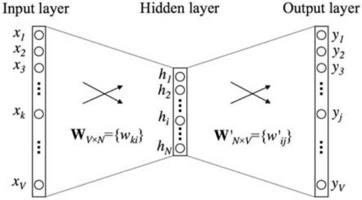

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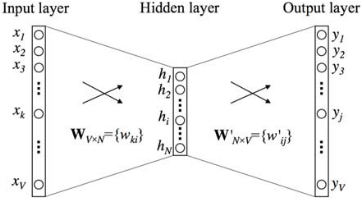

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The embedding vector for a given word is a row of W_I.

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$\rightarrow$ probability should be one if the target always follows the context word; zero if it never does, etc.

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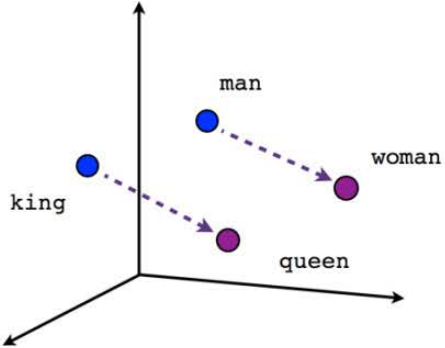
$$v_{\text{queen}} - v_{\text{woman}} + v_{\text{men}} \approx v_{\text{king}}$$



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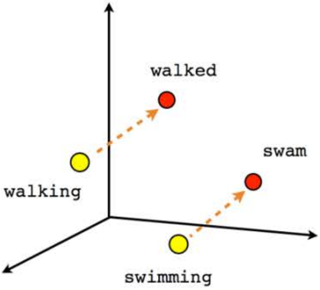
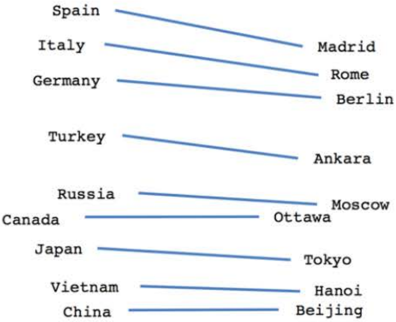


Verb tense



Country-Capital

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Shows excellent performance on many tasks (better than CBOW).

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Can we provide framework for embeddings so we can talk about one word being statistically significantly different to another? (yes! Cho et al, 2018). And perhaps make embeddings dependent on covariates? (Rudolph et al, 2017; Rodriguez et al.)