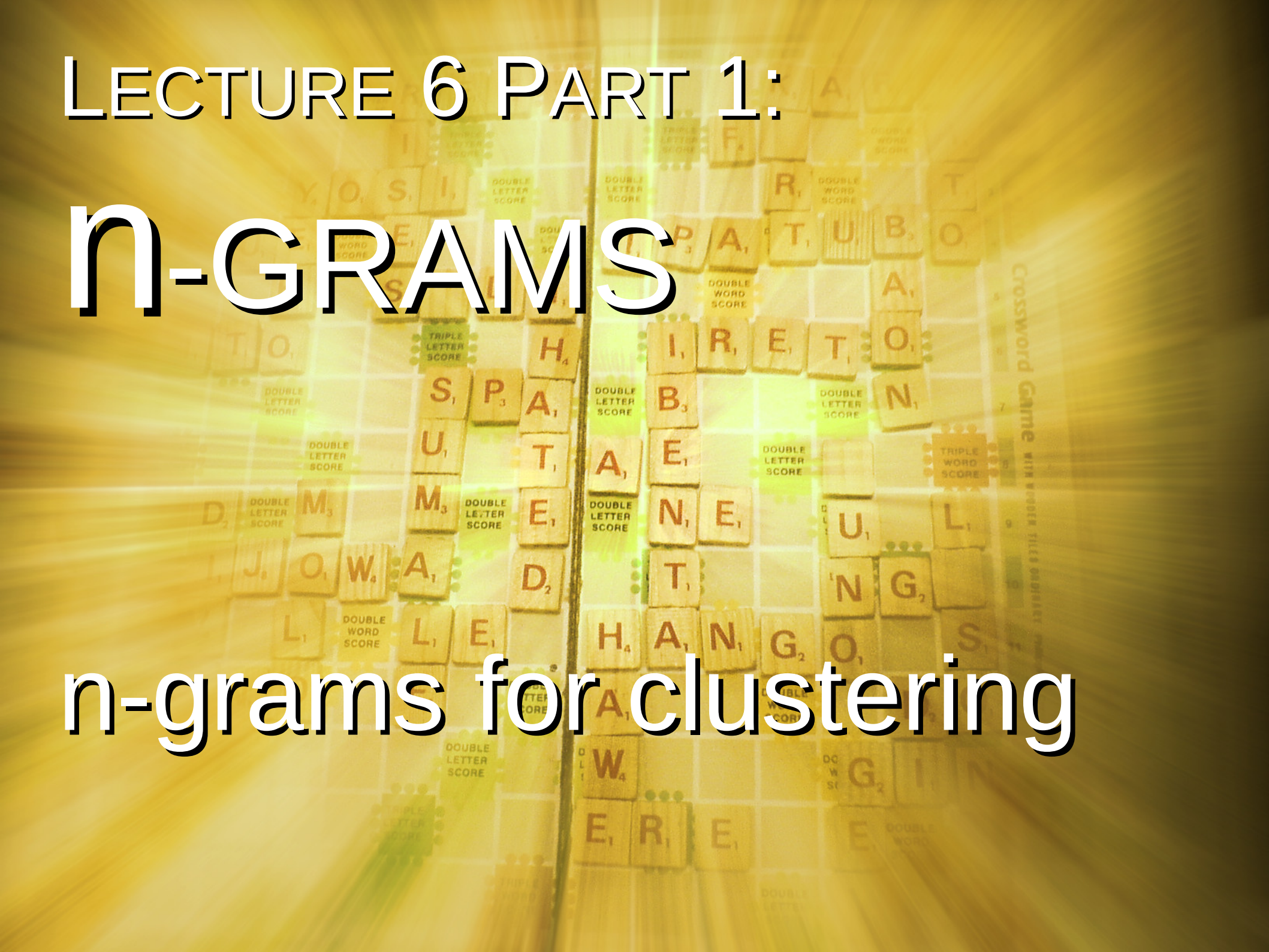


Lecture 6 Part 1:

n-grams

n-grams for clustering

N-gram mixture models for clustering

- We have previously seen how mixtures of Gaussian distributions can be used to model groups of texts
- More generally, a mixture model can use any type of distribution to model the documents in each cluster. **N-grams can be used as the probability distribution within a cluster.**

N-gram mixture models for clustering

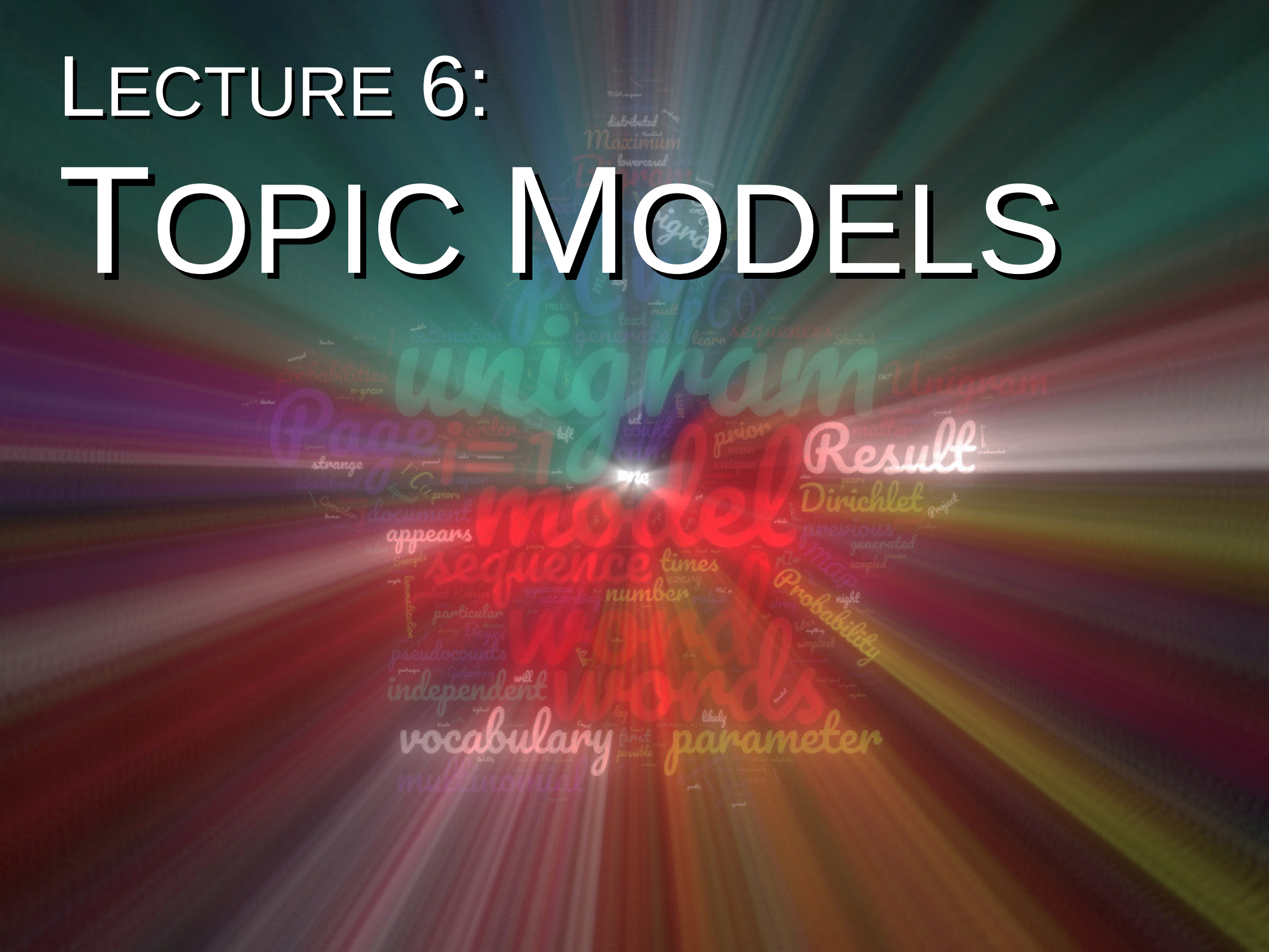
- Basic idea of the EM algorithm:
  - **E-step:** compute weights $\kappa_{ik} = p(k|\boldsymbol{w}^{(i)}) = \frac{p(k)\,p(\boldsymbol{w}^{(i)}|k)}{\sum_{k'=1}^{K} p(k')\,p(\boldsymbol{w}^{(i)}|k')}$ where $p(\boldsymbol{w}^{(i)}|\boldsymbol{\theta}_k)$ is the n-gram probability for document i using the n-gram probabilities in cluster k.
  - **M-step:** for each cluster k, use equations on the previous slides to optimize the N-gram parameters, but multiply transition counts from document i by κ_{ik} . Example for bigrams:

$$\theta_{ML,unigram|k} = \left[\frac{\sum_{i=1}^{M} \kappa_{ik} n_{1|i,unigram}}{\sum_{i=1}^{M} \kappa_{ik}}, \ldots, \frac{\sum_{i=1}^{M} \kappa_{ik} n_{V|i,unigram}}{\sum_{i=1}^{M} \kappa_{ik}} \right]$$

$$\theta_{ML,w|k} = \left[\frac{\sum_{i=1}^{M} \kappa_{ik} n_{1|w,i}}{\sum_{i=1}^{M} \kappa_{ik} n_{w|i}}, \ldots, \frac{\sum_{i=1}^{M} \kappa_{ik} n_{V|w,i}}{\sum_{i=1}^{M} \kappa_{ik} n_{w|i}} \right]$$

Lecture 6:

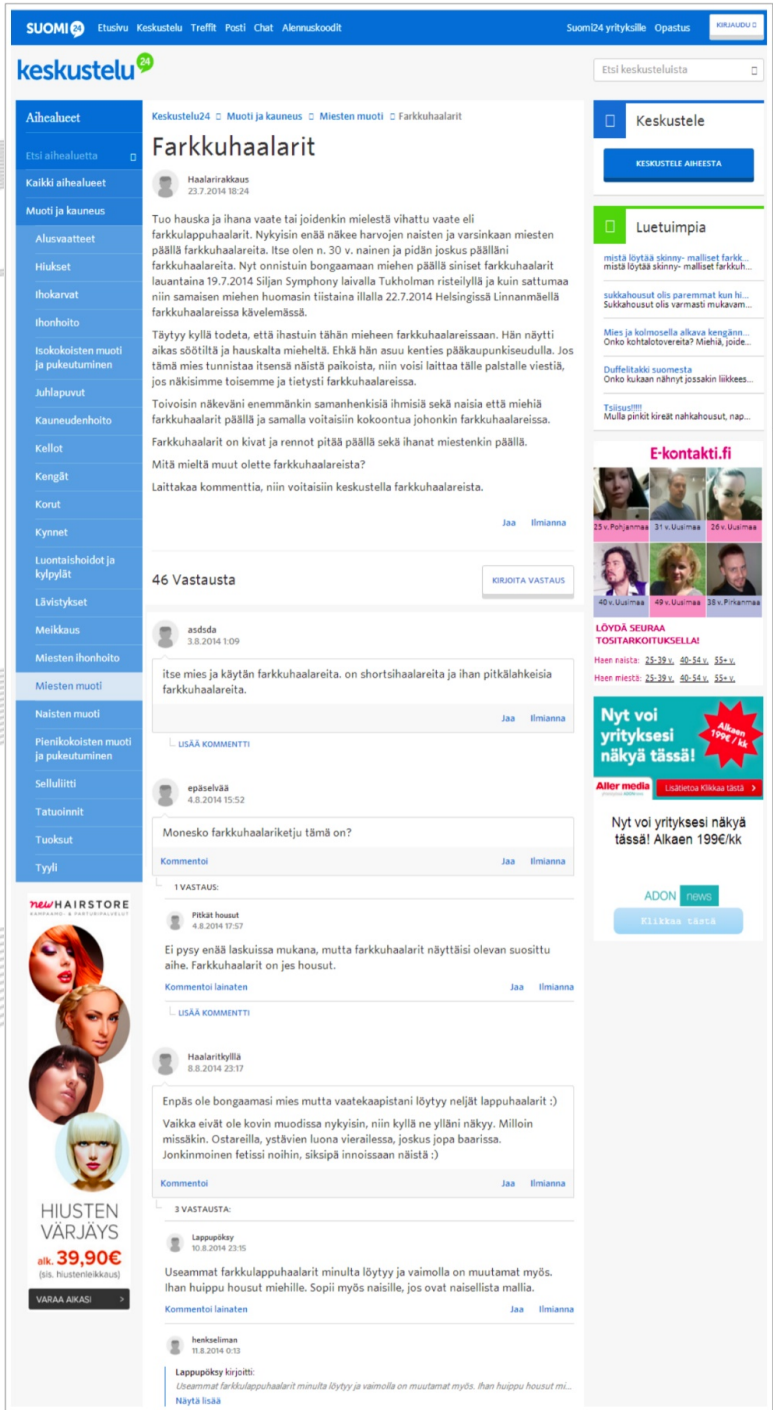
Topic Models



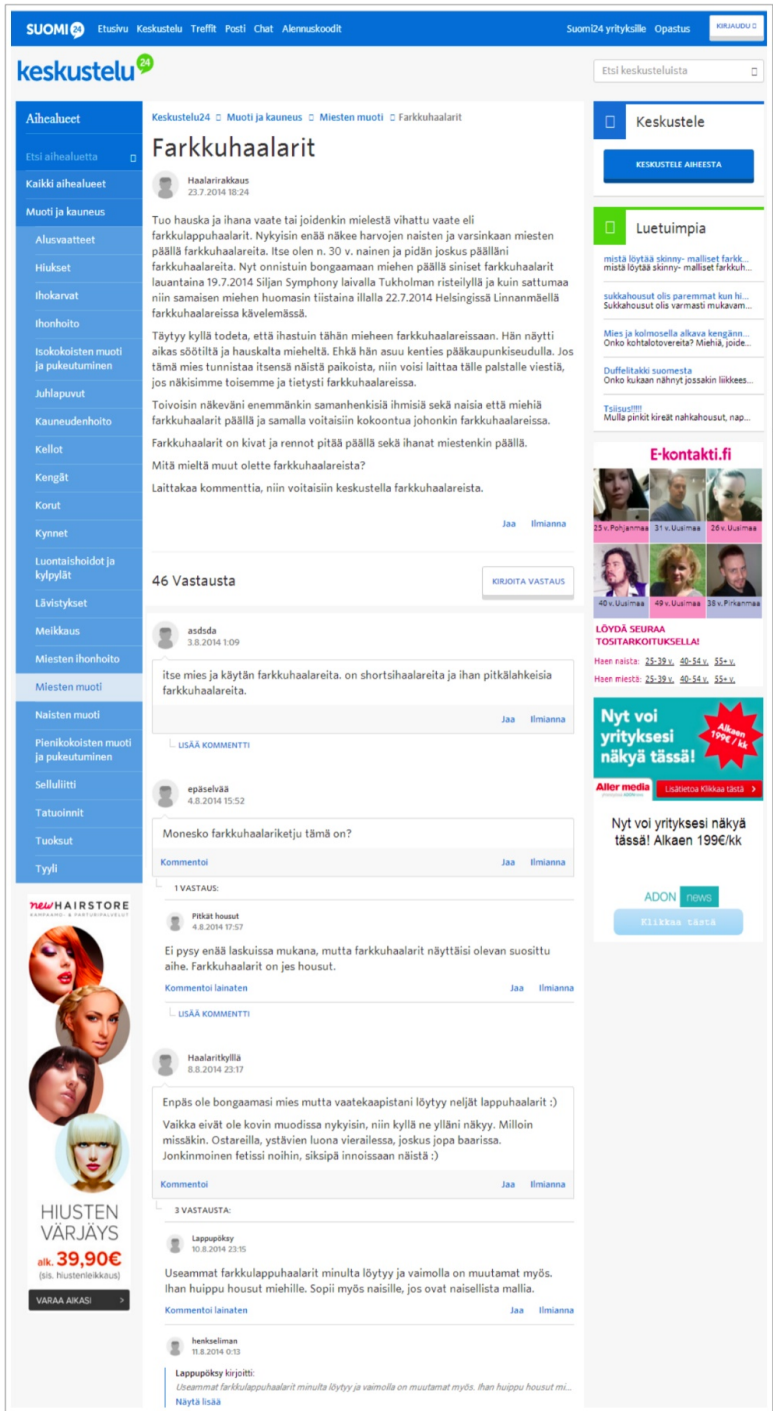
Text corpora

Suomi24

- One of Finland's most popular message forums
- 20 years of conversations 2001-2020
  - 2434 discussion areas
    - Over 5M discussion threads, 16M user names



Text corpora



Text corpora

Topic modeling: intuitive idea

Topic modeling: intuitive idea

Topic modeling: intuitive idea

Topic modeling: intuitive idea

? ? ? ?

Topic modeling: intuitive idea

Topic modeling: intuitive idea

? ? ? ?

Latent Semantic Analysis

- **Latent semantic analysis** (LSA; also called latent semantic indexing) is a statistical method to break a term frequency matrix into underlying factors.
- It is a vector-space based linear dimensionality reduction method for term-frequency vectors. It creates a low-rank approximation of a term-frequency matrix.
- Procedure: For M documents and V terms in the vocabulary,
  - Create a term-frequency matrix **X** (M rows, V columns)
  - Compute a singular value decomposition of the matrix:

$$\boldsymbol{X} = \boldsymbol{U}_{\text{Left}}\, \boldsymbol{D}\, \boldsymbol{U}_{\text{Right}}^{T}$$

$\boldsymbol{U}_{\text{Left}}$ is a M*K matrix of left eigenvectors, K=min(M,V)

$\boldsymbol{D}$ is a K*K diagonal matrix of singular values

$\boldsymbol{U}_{\text{Right}}$ is a V*K matrix of right eigenvectors

  - Take the largest few (e.g. k=20 largest) diagonal elements of D, take the corresponding columns of $\boldsymbol{U}_{\text{Left}}$ and $\boldsymbol{U}_{\text{Right}}$: call them $\hat{\boldsymbol{U}}_{\text{Left}}, \hat{\boldsymbol{D}}, \hat{\boldsymbol{U}}_{\text{Right}}$ (they are sized M*k, k*k and V*k respectively)

Latent Semantic Analysis

- Then $\hat{\boldsymbol{X}} = \hat{\boldsymbol{U}}_{\text{Left}} \hat{\boldsymbol{D}} \hat{\boldsymbol{U}}^T_{\text{Right}}$ approximates the original matrix
- Each document i (row i of **X**) is approximated as

$$\boldsymbol{X}[i,:] \doteq \hat{\boldsymbol{U}}_{\text{Left}}[i,:] \hat{\boldsymbol{D}} \hat{\boldsymbol{U}}^T_{\text{Right}} = \sum_{j=1}^{k} \hat{U}_{\text{Left}}[i,j] \hat{D}[j,j] \hat{\boldsymbol{U}}_{\text{Right}}[:,j]^T$$

- This approximation represents each document as a weighted combination of the columns of $\hat{\boldsymbol{U}}_{\text{Right}}$, so that
  - Each column of the M*k matrix $\hat{\boldsymbol{U}}_{\text{Left}}$ is a low-dimensional representation of a document
  - Each column of the V*k matrix $\hat{\boldsymbol{U}}_{\text{Right}}$ is a word-loading vector that represents a direction of variation in the data: which word counts tend to vary together
- LSA is the same as **principal component analysis** (PCA) on a covariance matrix of terms, computed from **X**, except that PCA substracts means, LSA does not
- LSA can also be applied to e.g. TF-IDF matrices


Take Me Out To The Ball Game

Latent Semantic Analysis

- Example code in Python:

```
#%% Try LSA on a very small data set
# Let's take the top-500 TF-IDF features,
# and 1000 documents of 20 Newsgroups
# (the rec.sport.baseball newsgroup)
dimensiontotals=numpy.squeeze( \
    numpy.array(numpy.sum(tfidfmatrix,axis=0)))
highesttotals=numpy.argsort(-1*dimensiontotals)
Xsmall=tfidfmatrix[:,highesttotals[0:500]]
Xsmall=Xsmall[9000:10000,:].todense()

# Compute 10 factors from LSA
n_low_dimensions=10
Uleft,D,UrightT=scipy.sparse.linalg.svds(\
    Xsmall,k=n_low_dimensions)
```

Latent Semantic Analysis

- Example code in Python:

```
# Examine the singular values
print(D)
Out: [ 76.78596317  82.07492002  91.14531964  98.92853817 113.17000393
 119.25390774 143.97132142 154.20292869 196.08939846 238.9600725 ]
# Examine a factor (here the one with largest singular value)
print(UrightT[9,:])
Out: [ 2.76185154e-18  3.33910697e-18 -1.36216218e-18 -3.12435117e-04
 -2.20575924e-18 -3.80957762e-05 -4.17970680e-18  1.03556854e-18
 -1.33681293e-18  8.83776226e-19  4.67368313e-18  2.91952229e-18
  4.23182966e-18 -1.23820240e-18  7.28796702e-19 -1.21670041e-18
 -4.82451750e-05 -1.02934627e-05 -2.71219158e-18 -3.78173411e-05
 -3.96785618e-18  2.76640163e-19 -1.03155284e-05 -3.21182175e-08
 -1.76191160e-18  1.71208356e-18 -1.34796924e-06  2.08766247e-18

# 20 words with largest absolute weights in the factor
topweights_indices=numpy.argsort(-1*numpy.abs(UrightT[9,:]))
print(remainingvocabulary[highesttotals[topweights_indices[0:20]]])
['gant' 'plate' 'dale' 'cub' 'inning' 'earlier' 'dispute' 'randy'
 'subscribe' 'struggle' 'ridiculous' 'glad' 'ab' 'ml' 'defensive' 'stl'
 'impression' 'bond' 'wayne' 'complaint']
# Same for the next highest factor
topweights_indices=numpy.argsort(-1*numpy.abs(UrightT[8,:]))
print(remainingvocabulary[highesttotals[topweights_indices[0:20]]])
['cub' 'inning' 'sox' 'idle' 'baltimore' 'era' 'stl' 'friday' 'houston'
 'saturday' 'bond' 'florida' 'minnesota' 'august' 'gant' 'ab' 'angel'
 'weekend' 'wilson' 'aaron']
```

Probabilistic Latent Semantic Analysis

- **Probabilistic latent semantic analysis** (PLSA; also called probabilistic latent semantic indexing) is a probabilistic model of co-occurrences of words and documents.
  - References:
    - Thomas Hofmann. **Probabilistic Latent Semantic Indexing**. In *Proceedings of the International Conference on Research and Development in Information Retrieval*, 1999.
    - Thomas Hofmann. **Unsupervised Learning by Probabilistic Latent Semantic Analysis**. *Machine Learning*, 42, 177-196, 2001
- Consider a collection with a set of M documents d and a vocabulary with a set of V words w. PLSA models the **co-occurrence** of a particular word in a particular document

Probabilistic Latent Semantic Analysis

- The joint probability of d and w is modeled given underlying latent classes t: the probabilities of d and w are assumed to become **independent** given the class. "If I know what I'm talking about, where I am has no effect on what I say!"

$$p(w,d)=\sum_{t=1}^{T} p(t)\,p(d|t)\,p(w|t)=\sum_{t=1}^{T} \pi_t \psi_{d|t} \theta_{w|t}$$

- This can be rewritten as

$$p(w,d)=p(d)\,p(w|d)=p(d)\sum_{t=1}^{T} p(t|d)\,p(w|t)=\pi_d \sum_{t=1}^{T} \psi_{t|d} \theta_{w|t}$$

- Here $\pi_d=p(d)$, $\psi_{t|d}=p(t|d)$, and $\theta_{w|t}=p(w|t)$ are probabilities of multinomial distributions which are parameters of the PLSA model.

Probabilistic Latent Semantic Analysis

- In a set of M documents, suppose document d_i has N_i word occurrences. The PLSA log-likelihood is:

$$\sum_{i=1}^{M}\sum_{j=1}^{N_i}\log p(w_j,d_i)=\sum_{i=1}^{M}\sum_{j=1}^{N_i}\log\left(\pi_i\sum_{t=1}^{T}\psi_{t|d}\theta_{w|t}\right)$$

- Another way to represent the same thing: if we count how many co-occurrences $n_{v,i}$ each vocabulary word v has in document i, the log-likelihood can be written as

$$\sum_{i=1}^{M}\sum_{v=1}^{V}n_{v,i}\log\left(\pi_i\sum_{t=1}^{T}\psi_{t|d}\theta_{w|t}\right)$$

- Each word occurrence comes from one topic t, which can be seen as a latent variable. PLSA can be fitted to a set of documents by maximum likelihood using the **Expectation-Maximization algorithm.**

Probabilistic Latent Semantic Analysis

- **E-step:** for each pair v, d_i compute the conditional topic distribution

$$\kappa_{t|v,i} = p(t|v,d_i) = \frac{p(v,d_i,t)}{p(v,d_i)} = \frac{p(v|t)\,p(t|d_i)\,p(d_i)}{p(v,d_i)}$$

$$= \frac{\theta_{v|t}\psi_{t|d_i}\pi_{d_i}}{\sum_{t'=1}^{T}\theta_{v|t'}\psi_{t'|d_i}\pi_{d_i}} = \frac{\theta_{v|t}\psi_{t|d_i}}{\sum_{t'=1}^{T}\theta_{v|t'}\psi_{t'|d_i}}$$

- **M-step:** optimize the parameters as

$$\pi_{n_i} = \frac{\sum_{v=1}^{V} n_{v,i}}{\sum_{i'=1}^{M}\sum_{v=1}^{V} n_{v,i'}} \qquad \psi_{t|d_i} = \frac{\sum_{v=1}^{V} n_{v,i}\kappa_{t|v,i}}{\sum_{v=1}^{V} n_{v,i}} \qquad \theta_{v|t} = \frac{\sum_{i=1}^{M} n_{v,i}\kappa_{t|v,i}}{\sum_{i=1}^{M}\sum_{v'=1}^{V} n_{v',i}\kappa_{t|v',i}}$$

These equations are simple to implement: no need for any complicated mathematical operations, just simple sums. The $\pi_d = p(d)$ only need to be computed once.

Probabilistic Latent Semantic Analysis

•**PLSA code in Python (there are also a number of existing implementations available online):**

```
import numpy, numpy.matlib, scipy, scipy.stats
def plsa(document_to_word_matrix, n_topics, n_iterations):
    n_docs=numpy.shape(document_to_word_matrix)[0]              # Number of documents and vocabulary words
    n_vocab=numpy.shape(document_to_word_matrix)[1]
    theta = scipy.stats.uniform.rvs(size=(n_vocab,n_topics))  # Prob of words per topic: random init
    theta = theta/numpy.matlib.repmat(numpy.sum(theta,axis=0),n_vocab,1)
    psi = scipy.stats.uniform.rvs(size=(n_topics,n_docs))      # Probs topics per document: random init
    psi = psi/numpy.matlib.repmat(numpy.sum(psi,axis=0),n_topics,1)
    n_words_in_docs = numpy.squeeze(numpy.array(\              # Numbers of words in documents: computed once
        numpy.sum(document_to_word_matrix,axis=1)))
    n_totalwords = numpy.sum(n_words_in_docs)                  # Total number of words: computed once
    pi = n_words_in_docs/n_totalwords                          # Document probs: computed once
    for myiter in range(n_iterations):                         # Perform Expectation-Maximization iterations
        # ===Perform E-step====
        doc_word_to_topics = []                # Compute theta_{v|t}psi_{t|d}/sum_t' theta_{v|t'}psi_{t'|d}
        doc_word_to_topic_sum = numpy.zeros((n_docs,n_vocab))
        for t in range(n_topics):
            doc_word_to_topict = \
                numpy.matlib.repmat(theta[:,t],n_docs,1) * \
                numpy.matlib.repmat(psi[t,:],n_vocab,1).T
            myepsilon=1e-14           # Add a positive number to avoid divisions by zero
            doc_word_to_topict += myepsilon
            doc_word_to_topics.append(doc_word_to_topict)
            doc_word_to_topic_sum += doc_word_to_topict
        for t in range(n_topics):
            doc_word_to_topics[t] /= doc_word_to_topic_sum
        # =======Perform M-step=======
        # Add a small number to word counts to avoid divisions by zero
        for t in range(n_topics):                              # Compute document-to-topic probabilities.
            psi[t,:] = numpy.squeeze(numpy.array(numpy.sum( \
               numpy.multiply(document_to_word_matrix+myepsilon,doc_word_to_topics[t]),axis=1)))
        psi /= numpy.matlib.repmat(numpy.sum(psi,axis=0),n_topics,1)
        for t in range(n_topics):                              # Compute topic-to-word probabilities
            theta[:,t]= numpy.squeeze(numpy.array(numpy.sum( \
                 numpy.multiply(document_to_word_matrix,doc_word_to_topics[t]),axis=0).T))
        theta /= numpy.matlib.repmat(numpy.sum(theta,axis=0),n_vocab,1)
    return(pi,psi,theta)
```

Probabilistic Latent Semantic Analysis

- Example code in Python:

```
#%% Try PLSA on a very small data set
# Let's take the same 500 features as in LSI,
# and the same 1000 baseball documents but use
# the term-frequency (TF) values for the features
dimensiontotals=numpy.squeeze( \
    numpy.array(numpy.sum(tfidfmatrix,axis=0)))
highesttotals=numpy.argsort(-1*dimensiontotals)
Xsmall=tfmatrix[:,highesttotals[0:500]]
Xsmall=Xsmall[9000:10000,:].todense()

# Run PLSA
n_topics=10
n_iterations=200
pi,psi,theta=plsa(Xsmall, n_topics, n_iterations)
```

Probabilistic Latent Semantic Analysis

- Example code in Python:

```
# Examine the factor probabilities p(t) = sum_d p(t|d) p(d)
print(numpy.sum(psi*numpy.matlib.repmat(pi,n_topics,1),axis=1))
[0.11280546 0.11582869 0.09660424 0.10031745 0.11351756 0.09626955
 0.10611472 0.08149722 0.09108973 0.0859554 ]
# Examine a factor (here the one with largest probability, factor 1)
print(theta[:,1])
[0.00000000e+00 0.00000000e+00 0.00000000e+00 7.74240115e-15
 0.00000000e+00 4.15656746e-14 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 1.40467285e-14 9.66468649e-15 0.00000000e+00 8.85596500e-15
 0.00000000e+00 0.00000000e+00 8.66068367e-15 9.80049211e-15
# Words with largest absolute weights in the factor
topweights_indices=numpy.argsort(-1*numpy.abs(theta[:,1]))
print(remainingvocabulary[highesttotals[topweights_indices[0:20]]])
['inning' 'idle' 'minnesota' 'florida' 'fourth' 'saturday' 'eight' 'grab'
 'award' 'furthermore' 'mainly' 'effectively' 'supposedly' 'tx' 'ai'
 'combine' 'phenomenon' 'divide' 'lift' 'chief']
# Same for the next biggest factor (here factor 4)
topweights_indices=numpy.argsort(-1*numpy.abs(theta[:,4]))
print(remainingvocabulary[highesttotals[topweights_indices[0:20]]])
['bond' 'defensive' 'offensive' 'matt' 'dale' 'struggle' 'impression'
'conservative' 'lift' 'edward' 'sp' 'math' 'lewis' 'negative' 'widely'
 'politics' 'progress' 'significantly' 'terrible' 'related']
```

Probabilistic Latent Semantic Analysis

- In PLSA, content of an individual document is represented by the distribution

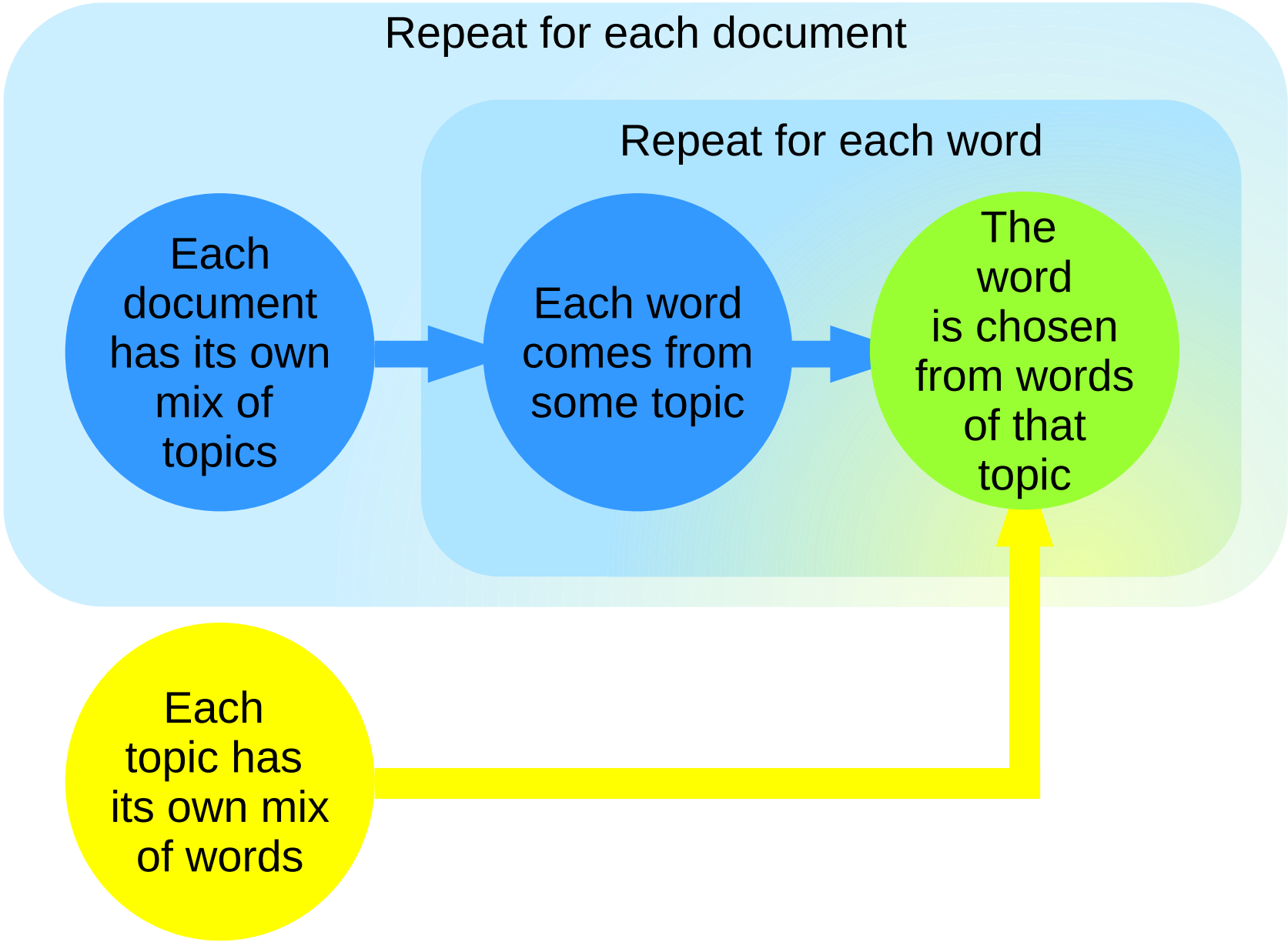
$$p(w|d) = \frac{p(w,d)}{p(d)} = \frac{p(d)\sum_{t=1}^{T} p(w|t)\,p(t|d)}{p(d)} = \sum_{t=1}^{T} \psi_{t|d}\,\theta_{w|t}$$

- Problem: PLSI is only a generative model of the observed set of documents - not of new documents!
  - PLSI defines $\psi_{t|d} = p(t|d)$ only over existing documents d, so one cannot derive what topics would exist in a new document

Latent Dirichlet Allocation

- Latent Dirichlet Allocation (LDA): a probabilistic model that discovers thematic topics underlying text documents, without requiring pre-existing definitions of what themes to look for.
  - Reference: David M. Blei, Andrew Y. Ng, and Michael I. Jordan. **Latent Dirichlet Allocation**. In *Proceedings of Neural Information Processing Systems 2002*.
- Topics are "building blocks" of text: each document is composed of a mixture of topics.
- This is different from mixture modeling:
  - In mixture modeling each document actually comes from only one underlying mixture component, even if it is uncertain which one.
  - In topic modeling each document really contains multiple topics at the same time.
- LDA is sometimes called a "discrete Principal Component Analysis"

Latent Dirichlet Allocation: plate model



Latent Dirichlet Allocation

- Probability of a word w occurring in a document d is a sum over a finite set of T topics:

$$p(w|d;\boldsymbol{\pi}_d)=\sum_{t=1}^{T} p(t|d)\,p(w|t)=\sum_{t=1}^{T} \pi_{t|d}\theta_{w|t}$$

- Here $\pi_{t|d}=p(t|d)$ is the probability (proportion, strength, prevalence) of topic t in document d, and $\theta_{w|t}=p(w|t)$ is the probability of word w in topic t. The $\pi_{t|d}$ and $\theta_{w|t}$ are parameters of the LDA model.
- The vector of topic probabilities $\boldsymbol{\pi}_d=\{\pi_{t|d}\}$ in the document is assumed to arise from a Dirichlet prior: $\boldsymbol{\pi}_d \sim Dirichlet(\boldsymbol{\alpha})$
- The probability of the word contents of a documentmust then be integrated over the possible topic probabilities

Latent Dirichlet Allocation

- Suppose document d_i has N_i word occurrences. Denote the word contents of the document by $\mathbf{d}_i$. The likelihood of the document contents is:

$$p(\boldsymbol{d}_i;\boldsymbol{\alpha},\Theta)=\int_{\boldsymbol{\pi}_{d_i}} p(\boldsymbol{\pi}_d|\boldsymbol{\alpha})\left(\prod_{j=1}^{N_i} p(w_j|d_i,\boldsymbol{\pi}_{d_i})\right)d\boldsymbol{\pi}_{d_i}$$

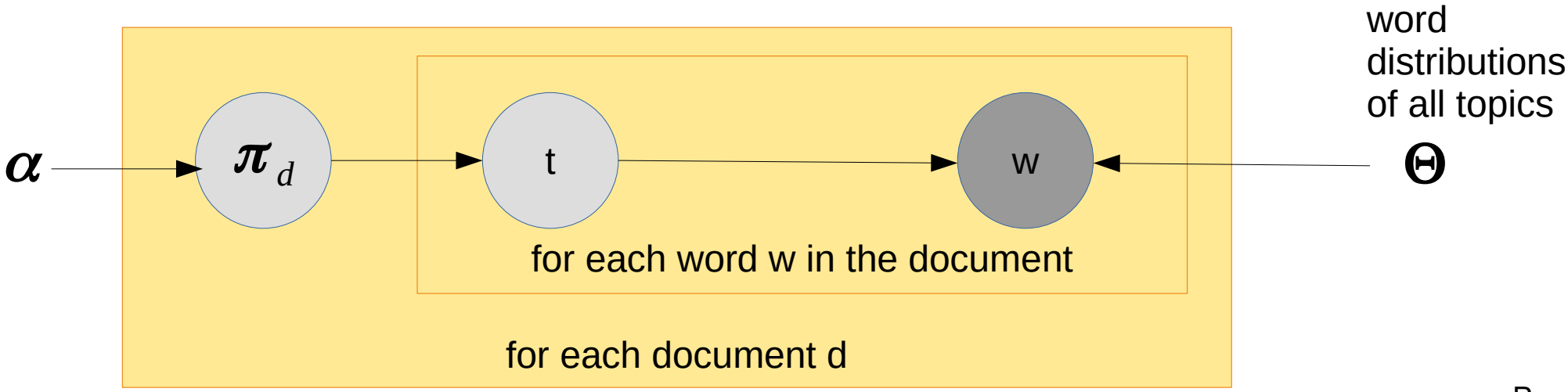
$$=\int_{\boldsymbol{\pi}_d} p(\boldsymbol{\pi}_d|\boldsymbol{\alpha})\left(\prod_{j=1}^{N_i}\left(\sum_{t=1}^{T}\pi_{t|d_i}\theta_{w_j|t}\right)\right)d\boldsymbol{\pi}_d$$

  and the likelihood of several documents is the product of the above terms for each: $\prod_{i=1}^{M} p(\boldsymbol{d}_i)$

- The topic probabilities are specific to each document but the word probabilities per topic are common to all documents.

Latent Dirichlet Allocation

- The corresponding plate model:



Latent Dirichlet Allocation

- This function is cannot be analytically computed, and is complicated to optimize for a set of data
- Two typical optimization approaches are used: **variational approximation** and **Gibbs sampling**
- Denote by $\mathbf{t}_d$ a vector containing the topic choice of each word in document d. Then the probability of the document content can be written as a sum over possible vectors $\mathbf{t}_d$

$$\log p(\boldsymbol{d};\boldsymbol{\alpha},\boldsymbol{\Theta}) = \log \int_{\boldsymbol{\pi}_d} \sum_{\boldsymbol{t}_d} p(\boldsymbol{w}_d|\boldsymbol{t}_d)\, p(\boldsymbol{t}_d|\boldsymbol{\pi}_d)\, p(\boldsymbol{\pi}_d|\boldsymbol{\alpha})\, d\boldsymbol{\pi}_d$$

- In variational approximation the idea is to compute an approximation of the posterior distribution of LDA parameters given data. The approximate distribution q( ) is assumed to have a simple form, and it is optimized to be close to the real posterior

$$\log p(\boldsymbol{d};\boldsymbol{\alpha},\boldsymbol{\Theta}) = \log \int_{\boldsymbol{\pi}_d} \sum_{\boldsymbol{t}_d} p(\boldsymbol{w}_d|\boldsymbol{t}_d)\, p(\boldsymbol{t}_d|\boldsymbol{\pi}_d)\, p(\boldsymbol{\pi}_d|\boldsymbol{\alpha}) \frac{q(\boldsymbol{\pi},\boldsymbol{t}_d;\gamma,\phi)}{q(\boldsymbol{\pi},\boldsymbol{t}_d;\gamma,\phi)}\, d\boldsymbol{\pi}_d$$

$$\geq E_q[\log p(\boldsymbol{w}_d|\boldsymbol{t}_d;\boldsymbol{\Theta}) + \log p(\boldsymbol{t}_d|\boldsymbol{\pi}_d) + \log p(\boldsymbol{\pi}_d;\boldsymbol{\alpha}) - \log q(\boldsymbol{\pi}_d,\boldsymbol{t}_d;\gamma,\phi)]$$

- The q( ) is chosen to be $q(\boldsymbol{\pi},\boldsymbol{t}_d;\gamma,\phi) = Dirichlet(\boldsymbol{\pi};\gamma) \prod_{i=1}^{N_d} Multinomial(z_i;\phi_i)$

Latent Dirichlet Allocation

- In Gibbs sampling the idea is:
  - Set $\mathbf{t}_d$ at first be some initial vector of topic choices for each word
  - For each word i, temporarily remove that word from its topic, and choose a new topic for it: compute for all k=1,...,T $p\left(t_i = k \middle| \boldsymbol{w}_d, \boldsymbol{t}_{d,-i}, \boldsymbol{\pi}_d, \Theta\right)$ where $\boldsymbol{t}_{d,-i}$ denotes the topic choices of all other words except i (when we are dealing with multiple documents, it would would denote topic choices of all other words in all documents), and then sample a new topic choice for i.
  - Do the same for other parameters

- However, in practice people usually use collapsed Gibbs sampling for LDA (reference: Thomas L Griffiths and Mark Steyvers. **Finding scientific topics**. *Proceedings of the National academy of Sciences of the United States of America*, 101(Suppl 1):5228–5235, 2004.)
- In collapsed Gibbs the idea is to also add a Dirichlet prior for the word distributions $\boldsymbol{\theta}_t$, and then integrate over the distributions $\boldsymbol{\pi}_d$ and Θ
- The result will be probabilities for resampling the topic-choice of each word, that only depend on topic-choices of the other words: $p\left(t_i = k \middle| \boldsymbol{w}_d, \boldsymbol{t}_{d,-i}\right)$
- This resampling is done for multiple iterations and then afterwards the topic model parameters can be computed as straightforward estimates based on the topic-assignments of words.

Latent Dirichlet Allocation

- There are several Python implementations of LDA: we will use the **Gensim** library implementation.
- Code:

```
import gensim
# Create a dictionary from the documents
startdoc=9000      # We will use the baseball n.g.
enddoc=10000       # again, but all features
gensim_docs=mycrawled_prunedtexts[startdoc:enddoc]
gensim_dictionary=gensim.corpora.Dictionary(gensim_docs)
# Create the document-term vectors
gensim_docvectors=[]
for k in range(len(gensim_docs)):
    docvector=gensim_dictionary.doc2bow(gensim_docs[k])
    gensim_docvectors.append(docvector)
```

Latent Dirichlet Allocation

- There are several Python implementations of LDA: we will use the **Gensim** library implementation.
- Code:

```
# Run the LDA optimization
numtopics=10
randomseed=124574527
numiters=10000
ninits=10
gensim_ldamodel=gensim.models.ldamodel.LdaModel( \
    gensim_docvectors, \
    id2word=gensim_dictionary,num_topics=numtopics, \
    iterations=numiters,random_state=randomseed)
```

Latent Dirichlet Allocation

- There are several Python implementations of LDA: we will use the **Gensim** library implementation.
- Code:

```
# Get topic content: term-topic probabilities
gensim_termtopicprobabilities=gensim_ldamodel.get_topics()
# Get topic prevalences per document, and overall topic prevalences
# (expected amount of documents per topic)
overallstrengths=numpy.zeros((numtopics,1))
documentstrengths=numpy.zeros((len(gensim_docvectors),numtopics))
for k in range(len(gensim_docvectors)):
    topicstrengths=gensim_ldamodel.get_document_topics(\
        gensim_docvectors[k],minimum_probability=0)
    for m in range(len(topicstrengths)):
        documentstrengths[k][topicstrengths[m][0]]=topicstrengths[m][1]
        overallstrengths[topicstrengths[m][0]]=\
        overallstrengths[topicstrengths[m][0]]+topicstrengths[m][1]
```

Latent Dirichlet Allocation

- There are several Python implementations of LDA: we will use the **Gensim** library implementation.
- Code:

```
# Show top-10 words of the top topic (number 5 here)
print(gensim_ldamodel.show_topic(5,topn=10))
[('mattingly', 0.011312583), ('sox', 0.010481743), ('idle', 0.010074499),
('williams', 0.008472339), ('rbi', 0.008317692), ('bond', 0.008116004),
('pitching', 0.006333267), ('batter', 0.00531599), ('batting', 0.004842933),
('sandberg', 0.0047366144)]

# Show top-10 words of the next strongest topic (number 4 here)
print(gensim_ldamodel.show_topic(5,topn=10))
[('winfield', 0.010770354), ('inning', 0.009858241), ('tiger', 0.00792999),
('clemens', 0.006710715), ('sox', 0.0063109742), ('boggs', 0.0054057315),
('hr', 0.005192798), ('era', 0.0049536), ('rbi', 0.0047922763), ('pitching',
0.004459158)]
```