The 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies

Interactive Topic Modeling

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June 20, 2011

Outline

- Introduction of Topic Models
- Diagnosing Topic Models
- Encoding Feedback to Topic Models
- Strategies
- Experiments
- Conclusion
- Future Steps

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Why topic models?

- A huge number of documents
- Want to know what's going on
- Don't have time to read

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Topic Models

- **A corpus-level view of major themes**
- **Unsupervised**

Conceptual approach

- What topics are expressed throughout the corpus
- What topics are expressed by each document

TOPIC 1

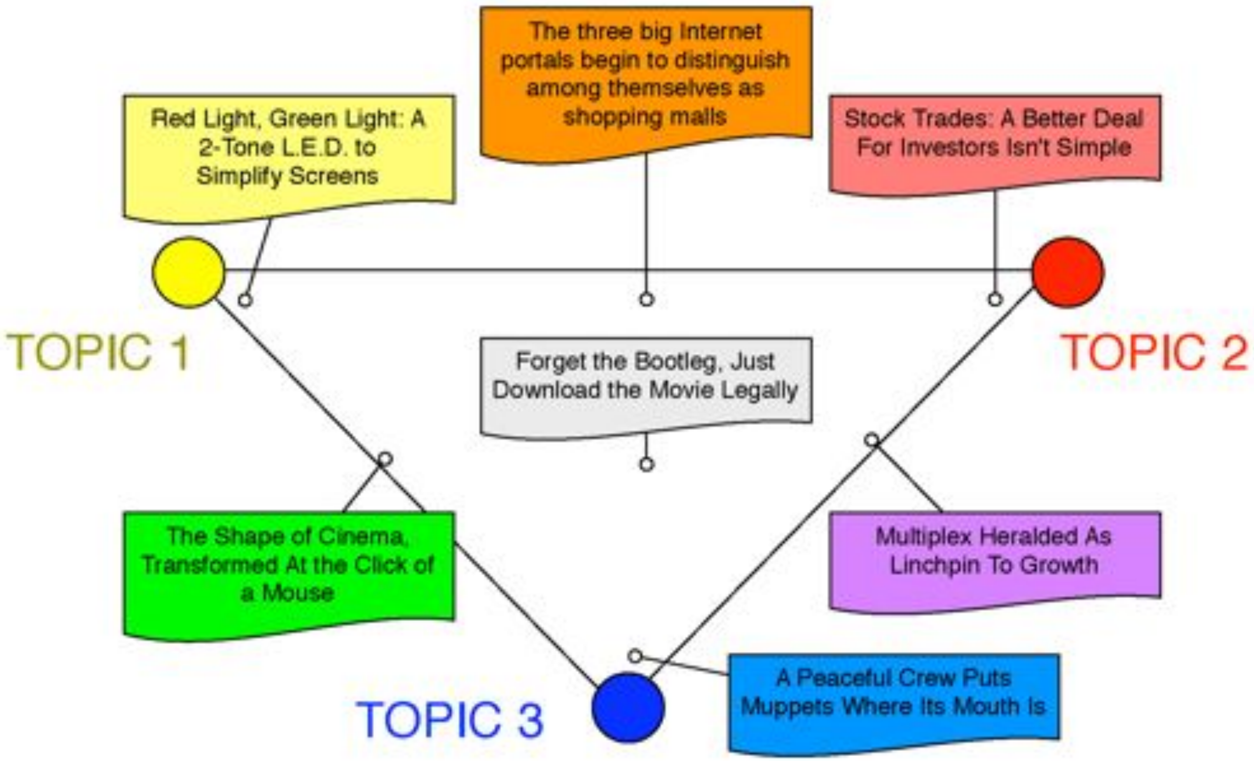
computer, site, technology, system, service, phone, internet, machine

TOPIC 2

Sell, sale, market, product, business, advertising, store

TOPIC 3

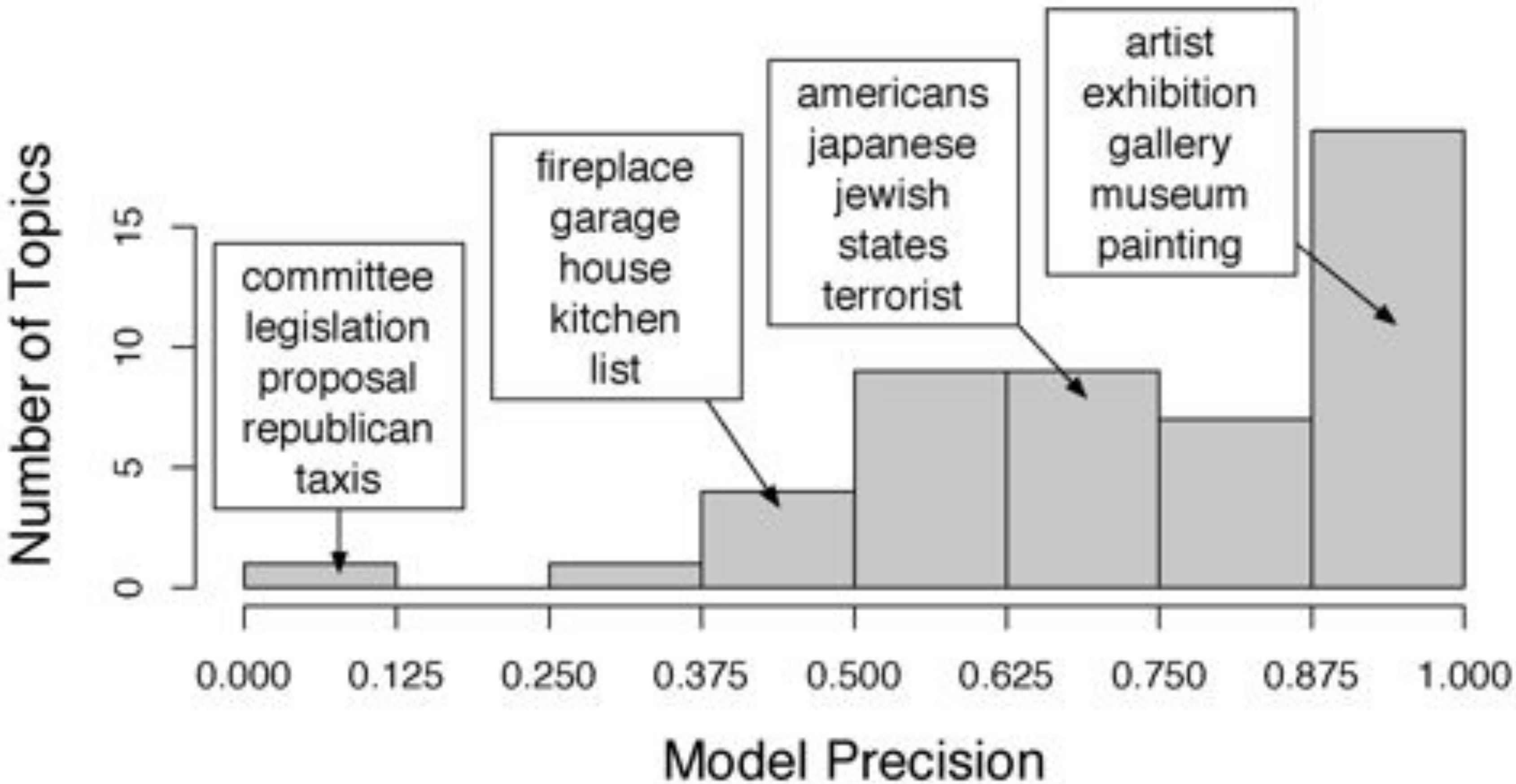
play, film, movie, theater, production, star, director, stage



What's Important?

- A generative probabilistic model of documents that posits a hidden topic structure
- Latent Dirichlet Allocation (LDA) (Blei et al., 2003)
  - A topic is a distribution over words
  - A document is a distribution over topics

What’s the problem?



- Measure topic quality (Chang et al., 2009), not all topics are good
- It is easy to be detected by humans

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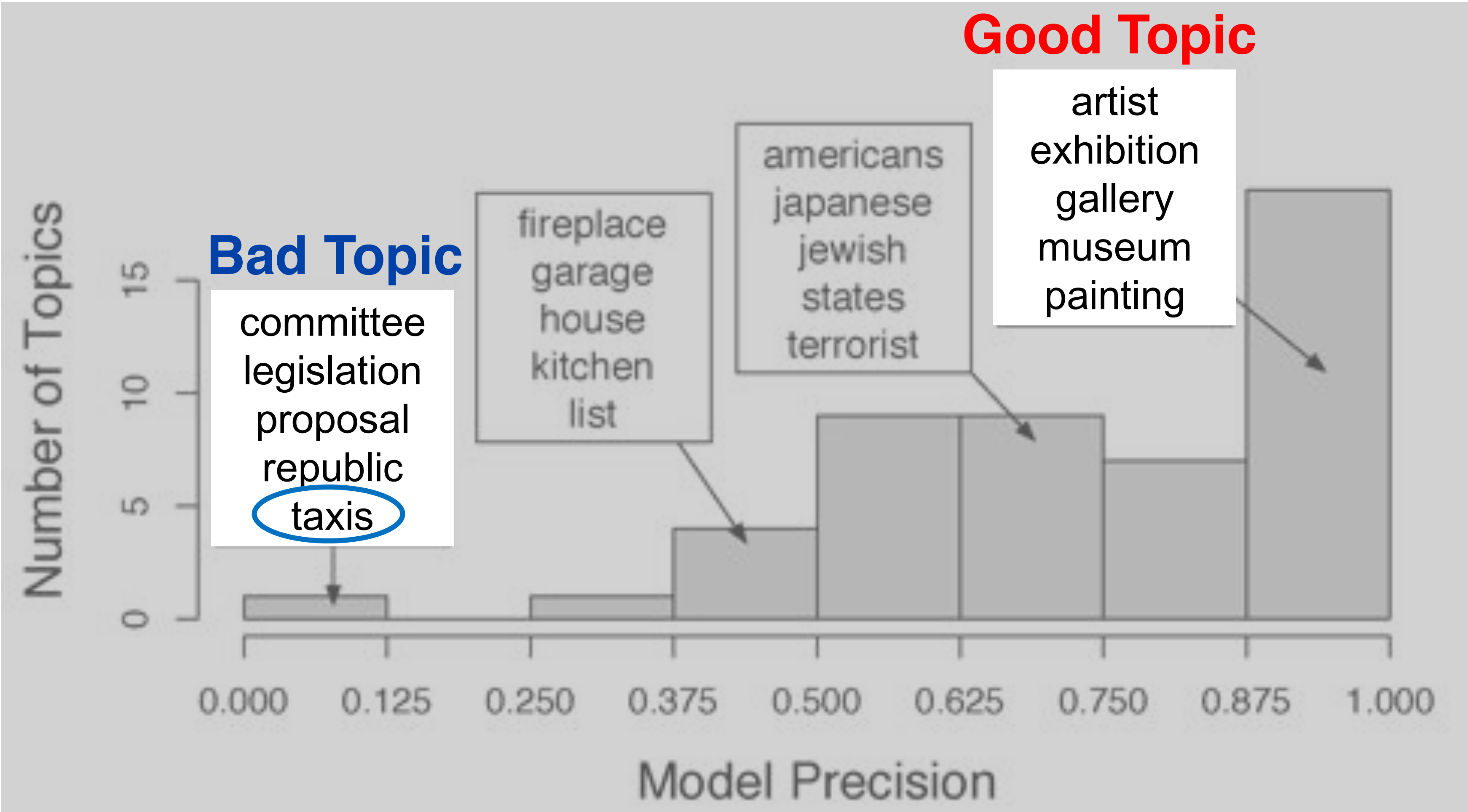

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Diagnosing topic models

Topic 1	Topic 2
shuttle	NASA
launch	telescope
racket	quasar
battledore	saturn
backhand	space
astronaut	moon

Diagnosing topic models

Topic 1	Topic 2
shuttle	NASA
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backhand	space
astronaut	moon

shuttle, launch and NASA should be together.

Diagnosing topic models

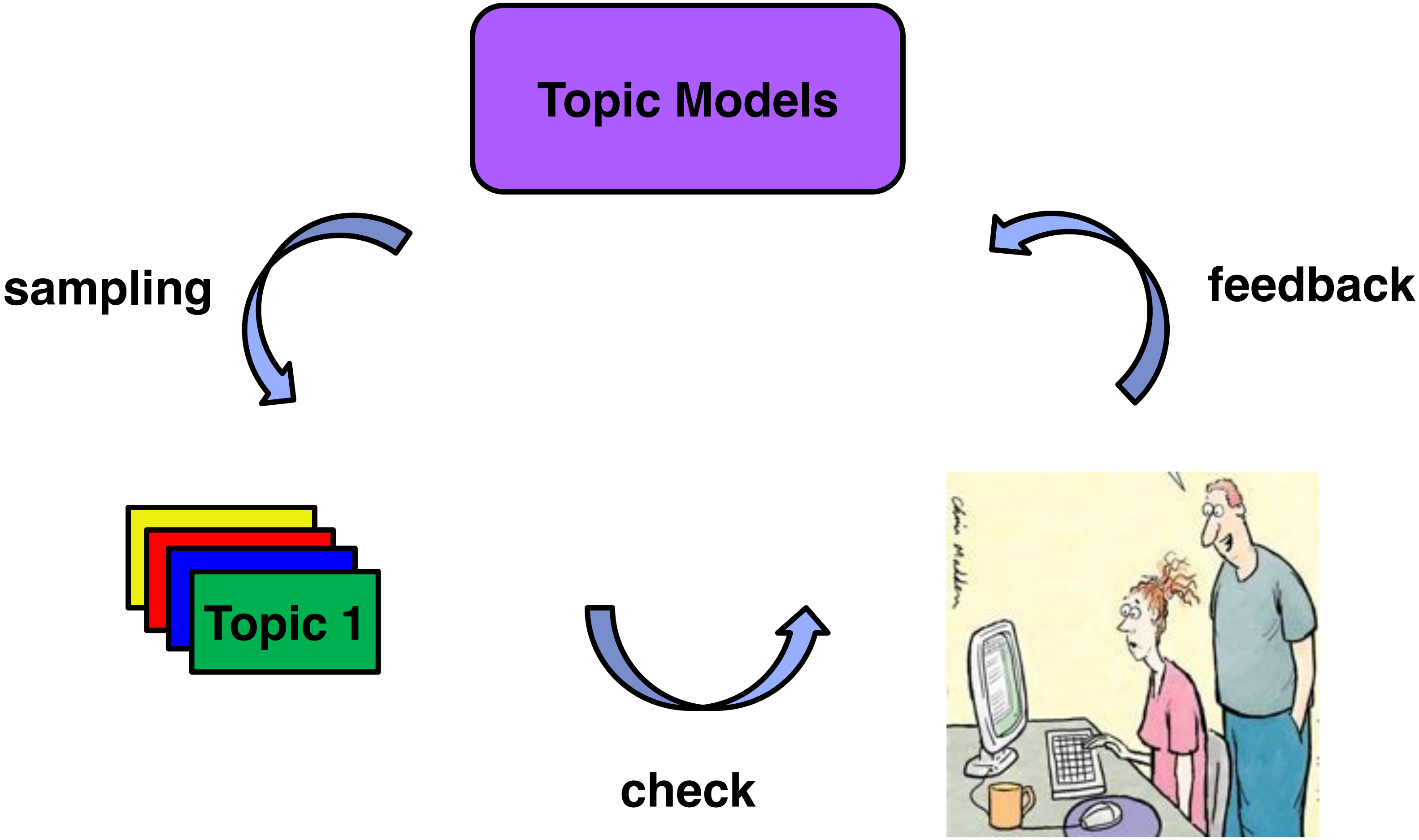
Topic 3
bladder
spinal_cord
sci
spinal
urinary
urothelial
cervical
urinary_tract
lumbar

Diagnosing topic models

Topic 3
bladder
spinal_cord
sci
spinal
urinary
urothelial
cervical
urinary_tract
lumbar

These words don't belong together! Should be separated.

Simple interaction



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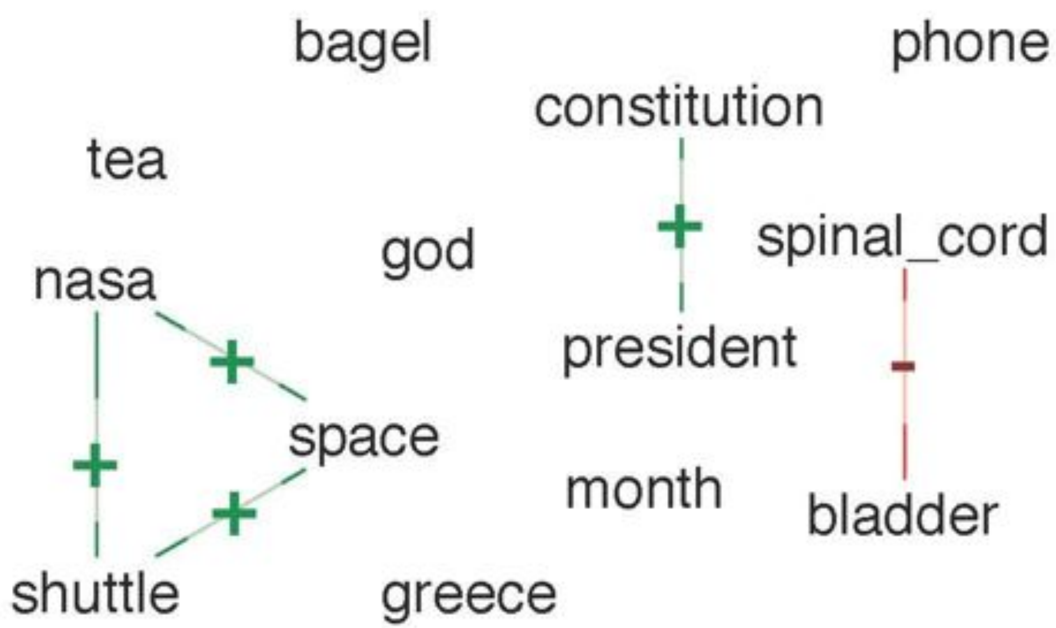
What feedback?

- Topics are distributions over uncorrelated words

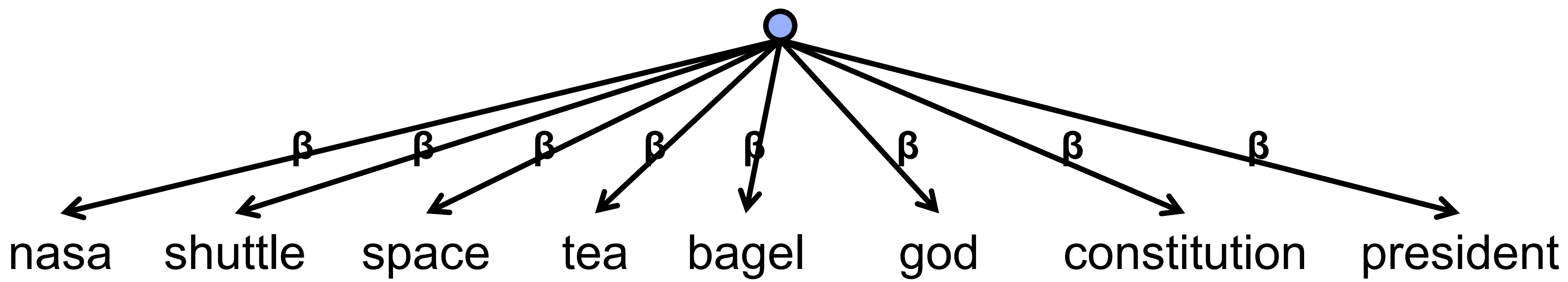
What feedback?

- Topics are distributions over uncorrelated words
- Add Constraints: positive and negative correlations



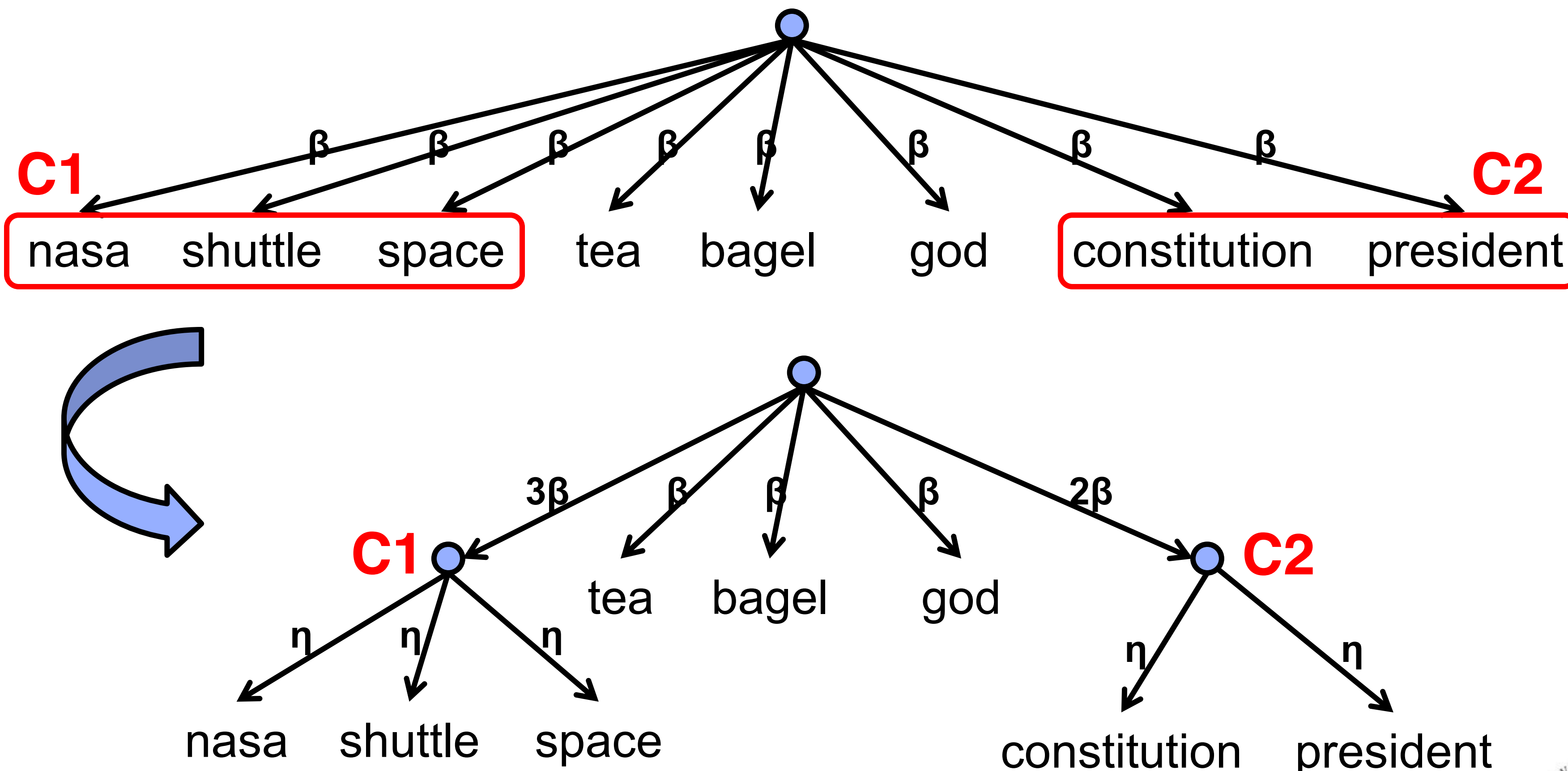
Prior in normal LDA

- Same prior for all the words (Boyd-Graber et al., 2007)



Model constraints as prior

- Dirichlet Forest: prior tree structure(Andrzejewski et al. 2009)
- Positive constraints only in this paper



How to incorporate feedback?

Start with same prior

Topic Models with a prior structure

Build prior structure

Incrementally topic learning

Topic 1

Get feedback from users

How to incorporate feedback?

Start with same prior

Topic Models with a prior structure

Build prior structure

Incrementally topic learning

How about the old topic assignment of each word?

Topic 1

Get feedback from users

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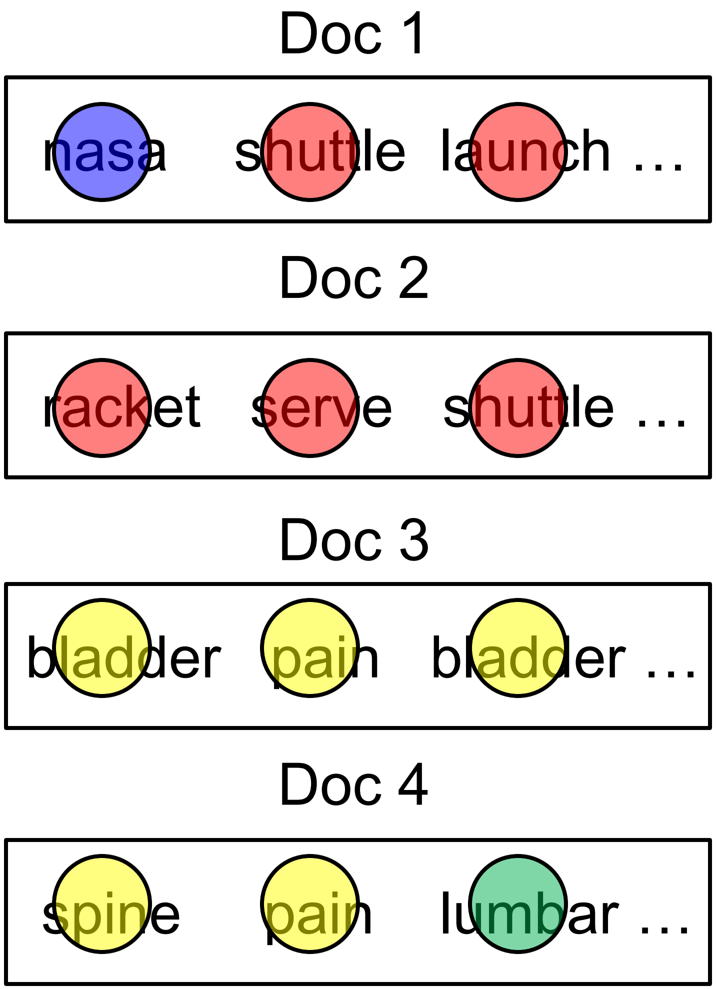
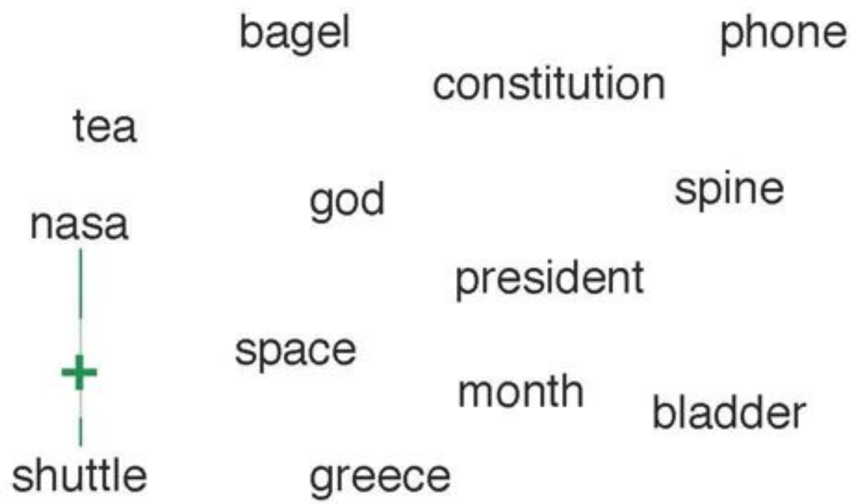
Remember or forget?

- Four strategies
  - All
  - None
  - Doc
  - Term
- Toy example

Toy example


Doc 1
nasa shuttle launch …
Doc 2
racket serve shuttle …
Doc 3
bladder pain bladder …
Doc 4
spine pain lumbar …


bagel
phone
constitution
tea
god
spine
nasa
president
space
month
bladder
shuttle
greece

Toy example: All

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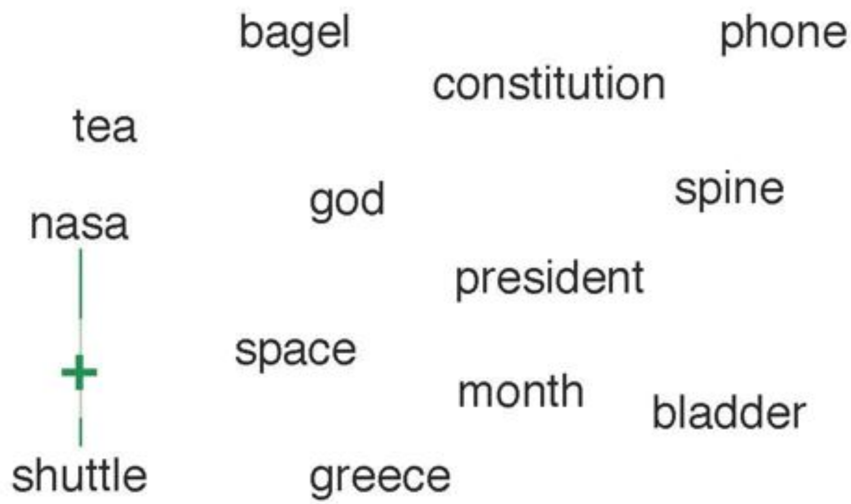


Strategy All

- Forget all topic assignments
- Start from the very beginning

Toy example: None

Doc 1

nasa shuttle launch …

Doc 2

racket serve shuttle …

Doc 3

bladder pain bladder …

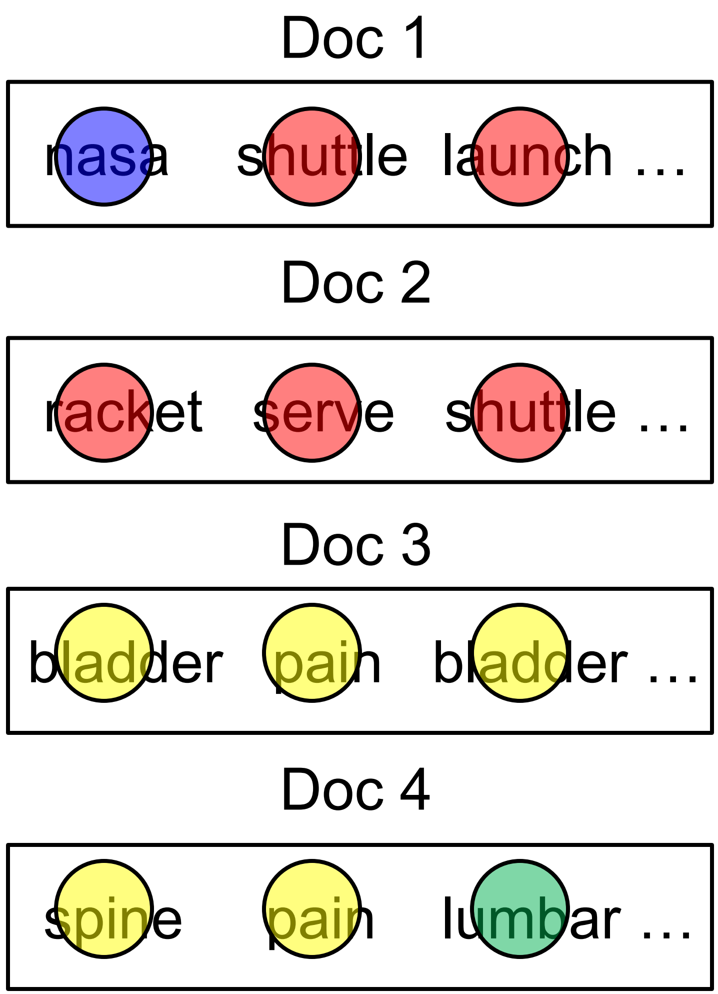
Doc 4

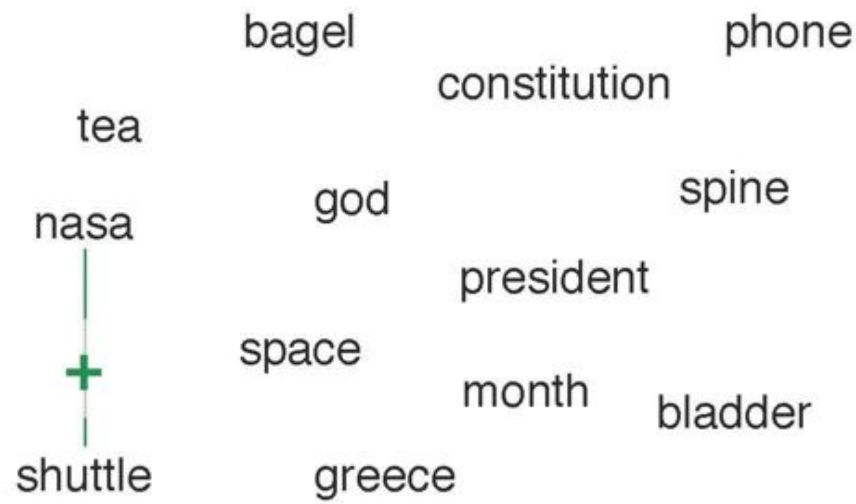
spine pain lumbar …

Strategy None

- Remember everything
- Continue

Toy example: Doc





Round 1

- Positive constr: (nasa - shuttle)
- Strategy: Doc

Toy example: Doc

Doc 1

nasa shuttle launch …

Doc 2

racket serve shuttle …

Doc 3

bladder pain bladder …

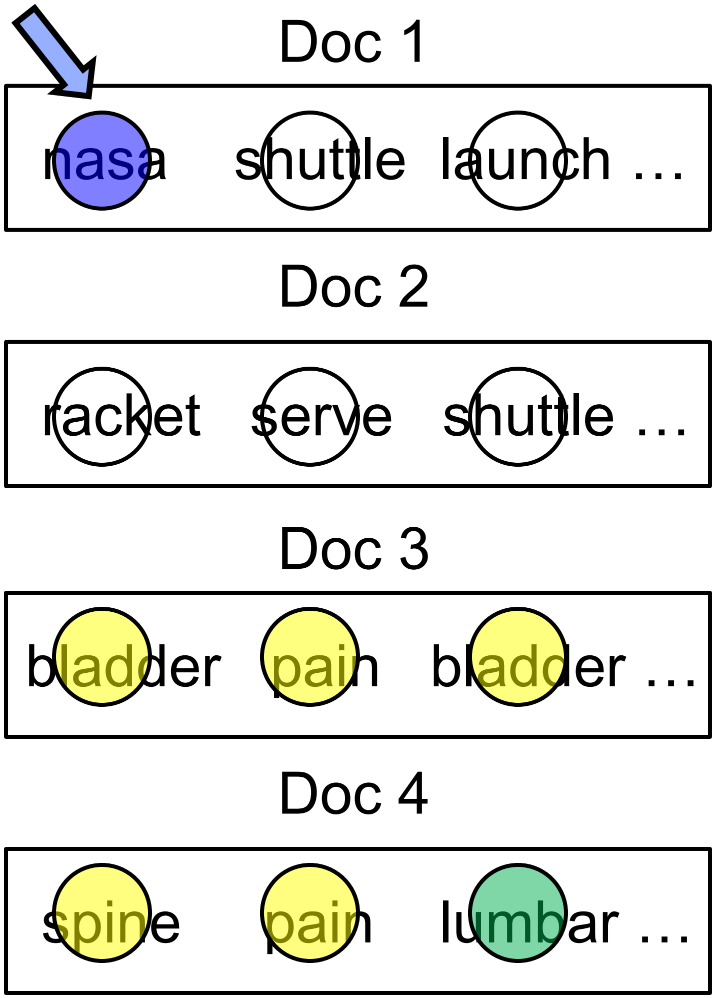
Doc 4

spine pain lumbar …

Strategy Doc

- Forget the topic assignments for docs containing constraints
- Remember the others
- continue

Toy example: Doc



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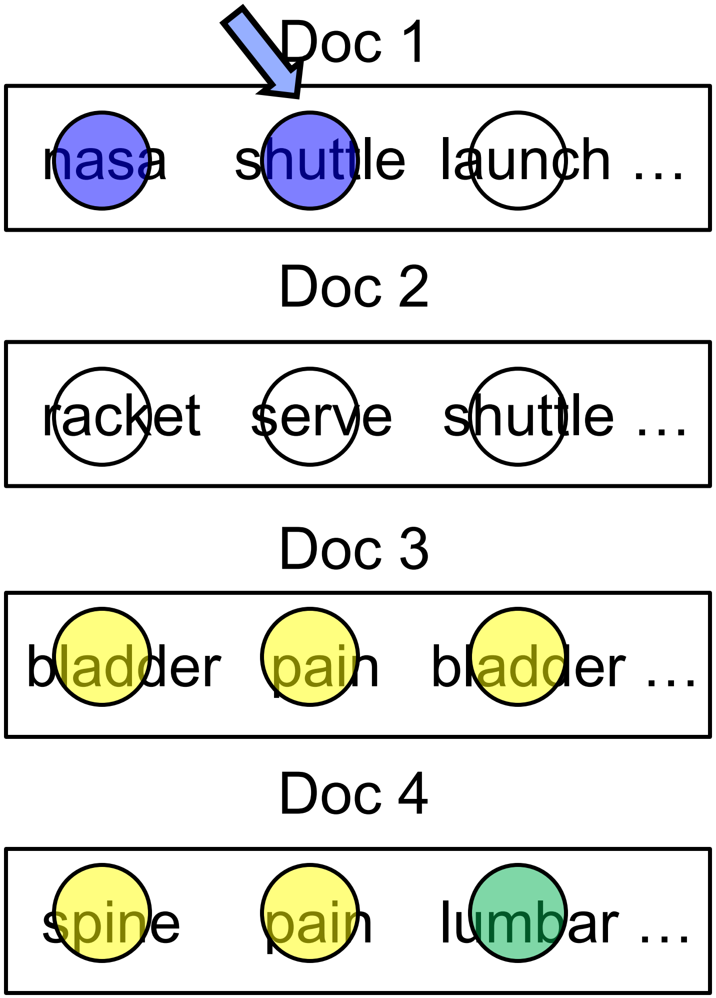

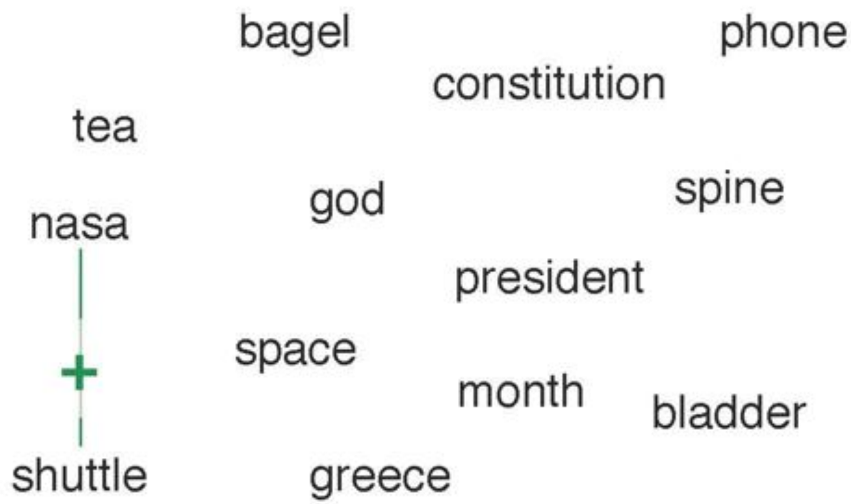

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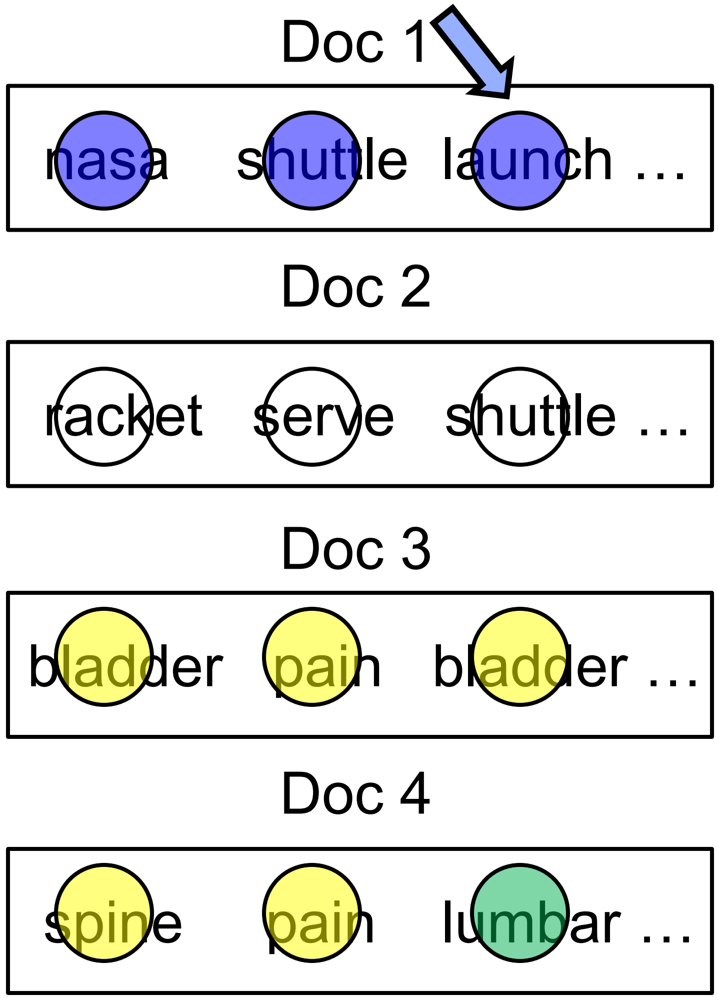

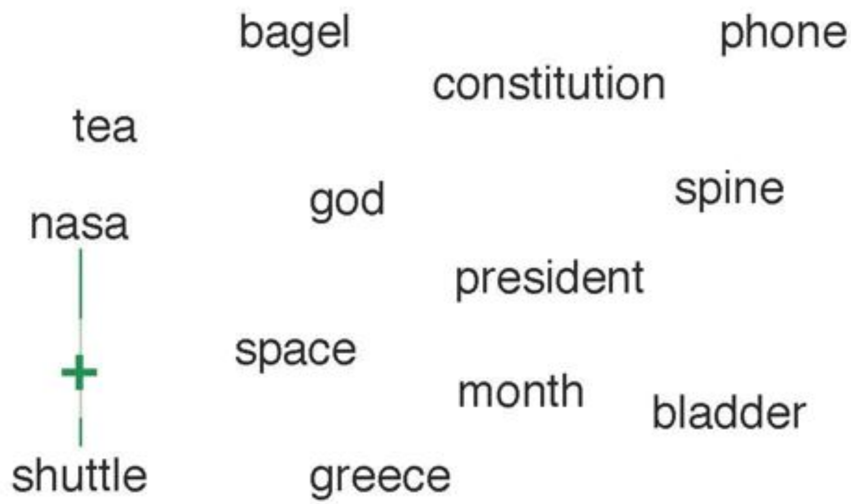

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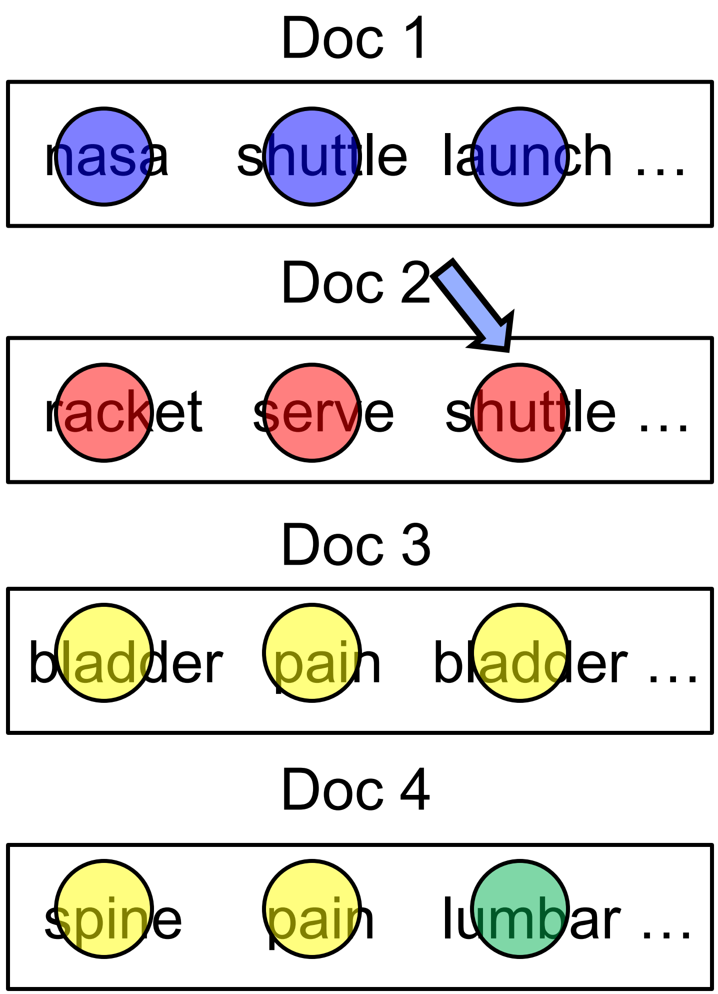

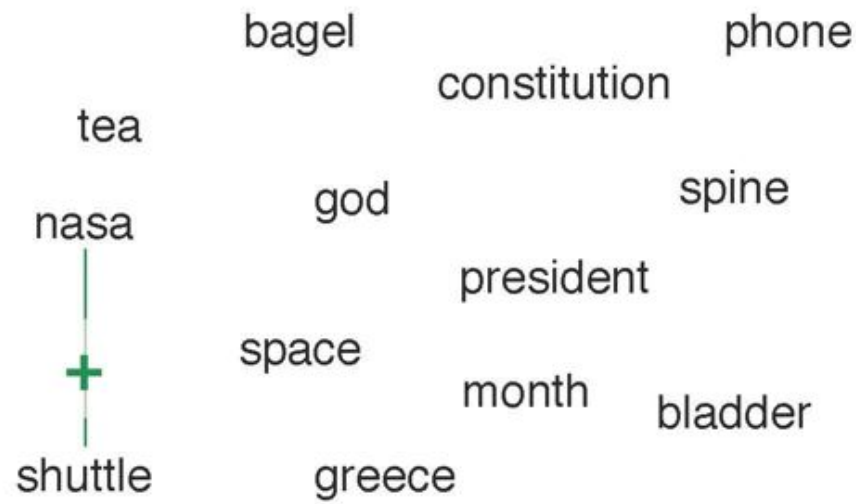

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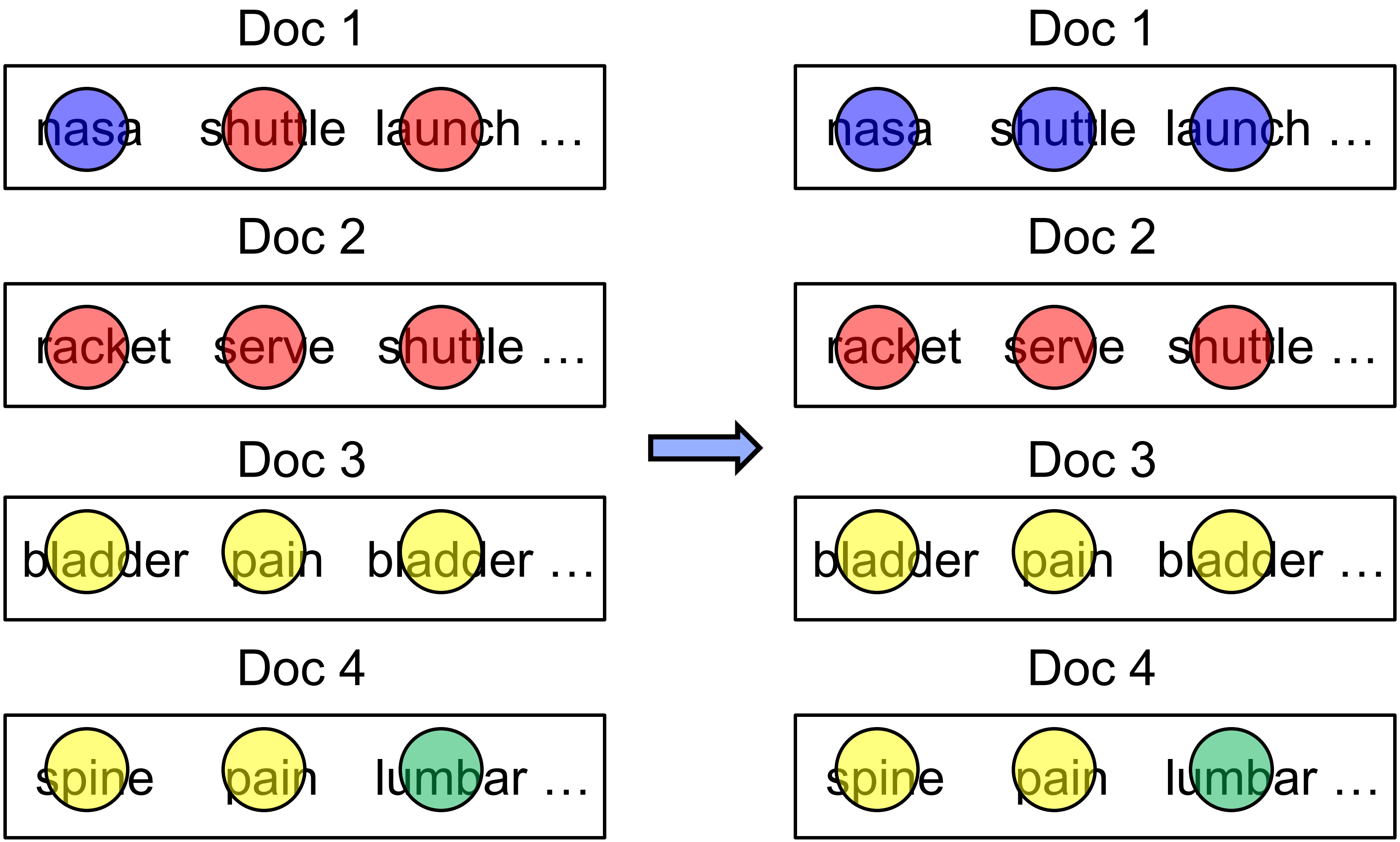
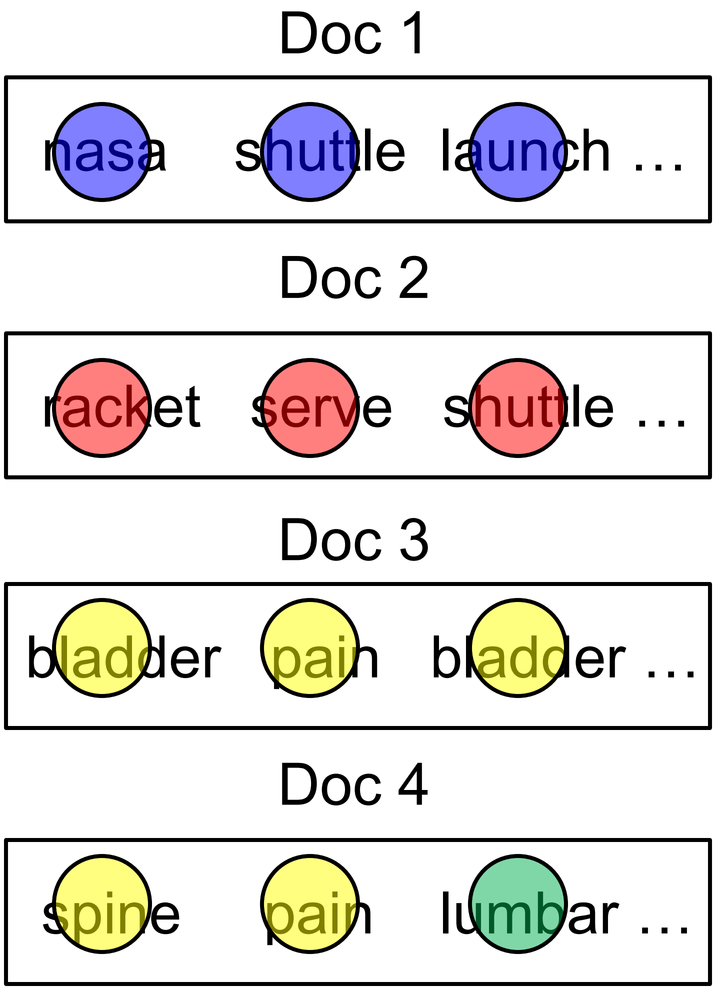
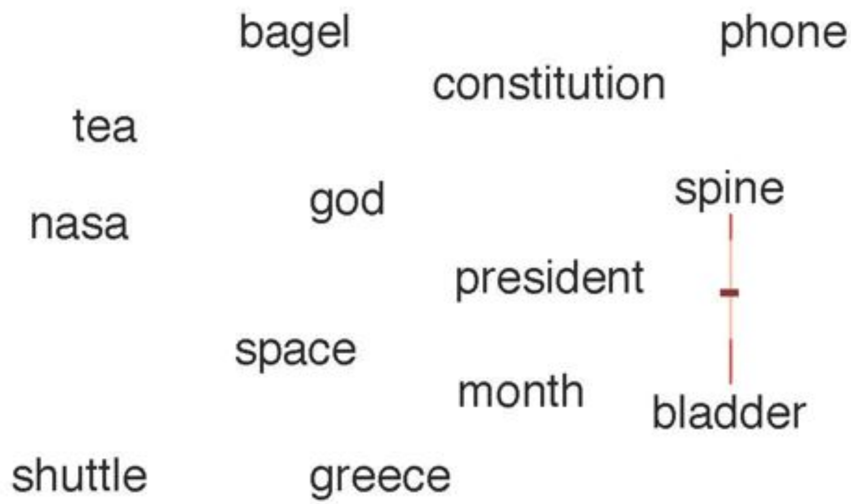
Toy example: Doc



Toy example: Term





Round 2

- Negative constr: (spine - bladder)
- Strategy: Term

Toy example: Term

Doc 1

nasa shuttle launch …

Doc 2

racket serve shuttle …

Doc 3

bladder pain bladder …

Doc 4

spine pain lumbar …

Strategy Term

- Forget the topic assignments for the constraint words,
- Remember the others
- Continue

Toy example: Term

Doc 1

nasa shuttle launch …

Doc 2

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Doc 3

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Doc 4

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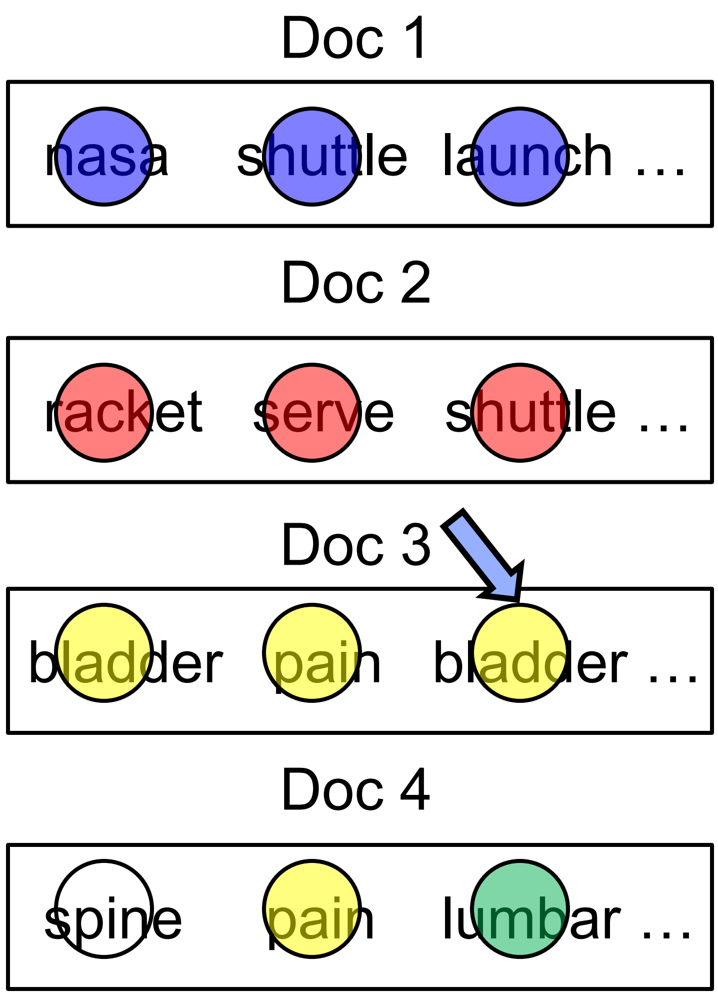
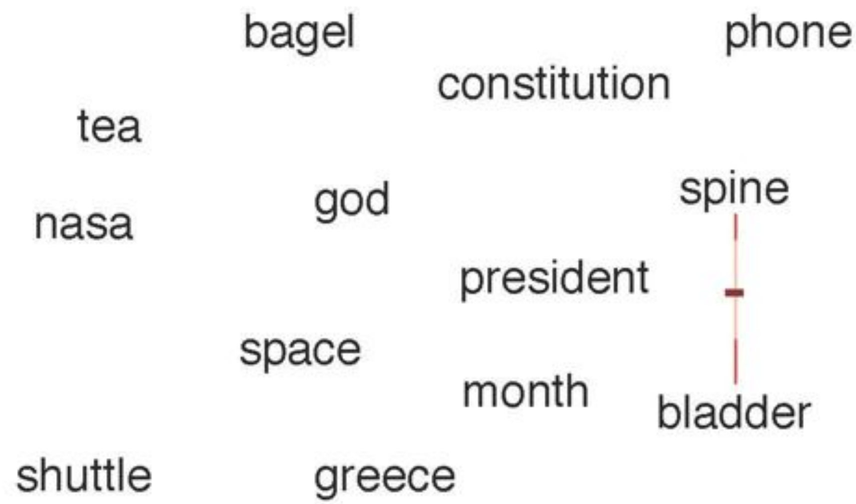
Round 2

- Negative constr: (spine - bladder)
- Strategy: Term

Toy example: Term

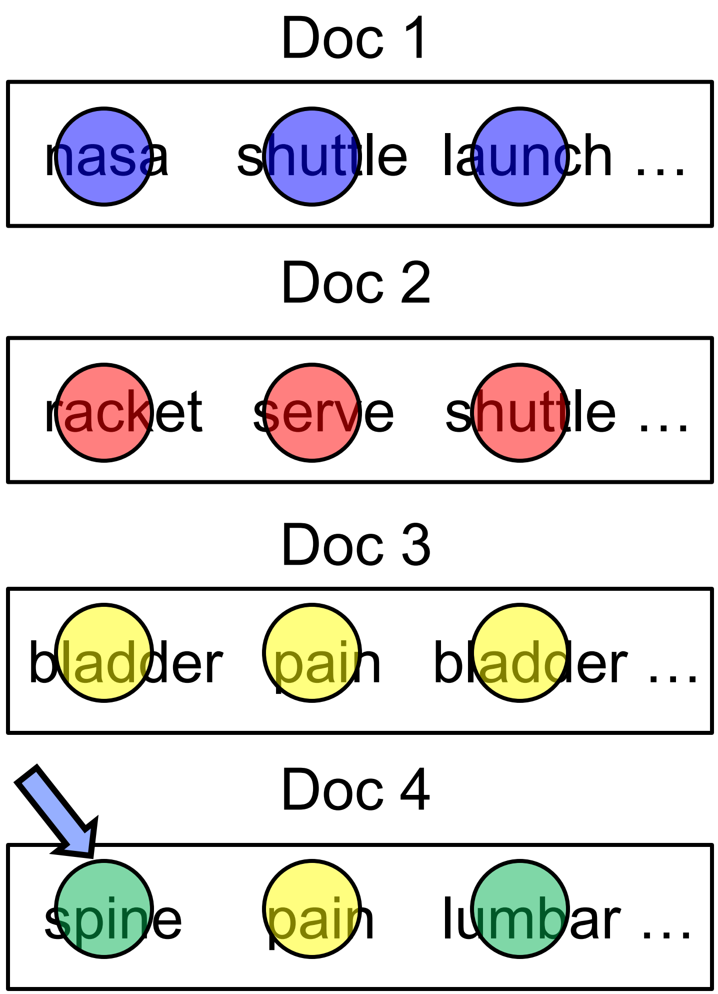


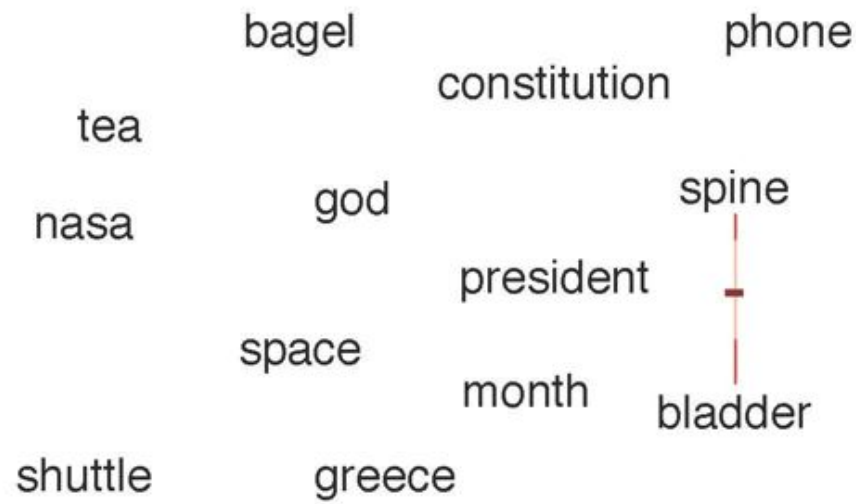


Round 2

- Negative constr: (spine - bladder)
- Strategy: Term

Toy example: Term





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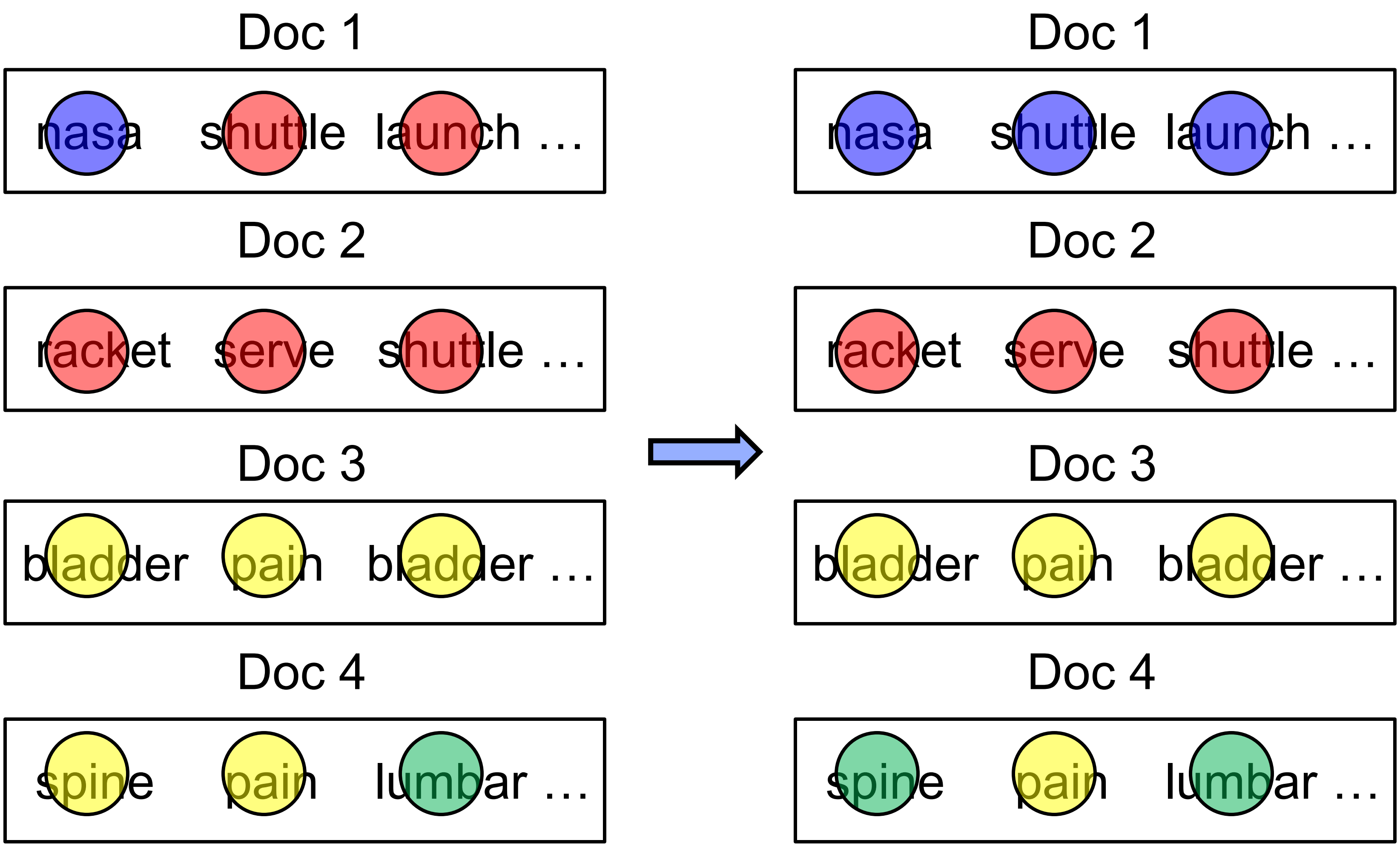

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Motivating example

Topic	Before
1	election, yeltsin, russian, political, party, democratic, russia, president, democracy, boris, country, south, years, month, government, vote, since, leader, presidential, military
2	new, york, city, state, mayor, budget, giuliani, council, cuomo, gov, plan, year, rudolph, dinkins, lead, need, governor, legislature, pataki, David
3	nuclear, arms, weapon, defense, treaty, missile, world, unite, yet, soviet, lead, secretary, would, control, korea, intelligence, test, nation, country, testing
4	president, bush, administration, clinton, american, force, reagan, war, unite, lead, economic, iraq, congress, america, iraqi, policy, aid, international, military, see
…	…
20	soviet, lead, gorbachev, union, west, mikhail, reform, change, europe, leaders, poland, communist, know, old, right, human, washington, western, bring, party

Motivating example

Topic	Before
1	election, yeltsin, russian, political, party, democratic, russia, president, military, democracy, boris, country, south, years, month, government, vote, since, leader, presidential
…	…
20	soviet, lead, gorbachev, union, west, mikhail, reform, change, europe, leaders, poland, communist, know, old, right, human, ashington, western, bring, party

Motivating example

Topic	Before
1	election, yeltsin, russian, political, party, democratic, russia, president, military, democracy, boris, country, south, years, month, government, vote, since, leader, presidential
…	…
20	soviet, lead, gorbachev, union, west, mikhail, reform, change, europe, leaders, poland, communist, know, old, right, human, ashington, western, bring, party

Suggested constraint

boris, communist, gorbachev, mikhail, russia, russian, soviet, union, yeltsin

Motivating example

Topic	Before	Topic	After
1	election, yeltsin, russian, political, party, democratic, russia, president, military, democracy, boris, country, south, years, month, government, vote, since, leader, presidential	1	election, democratic, south, country, president, party, africa, lead, even, democracy, leader, presidential, week, politics, minister, percent, voter, last, month, years
…	…	…	…
20	soviet, lead, gorbachev, union, west, mikhail, reform, change, europe, leaders, poland, communist, know, old, right, human, ashington, western, bring, party	20	soviet, union, economic, reform, yeltsin, russian, lead, russia, gorbachev, leaders, west, president, boris, moscow, europe, poland, mikhail, relations, communist, power

Motivating example

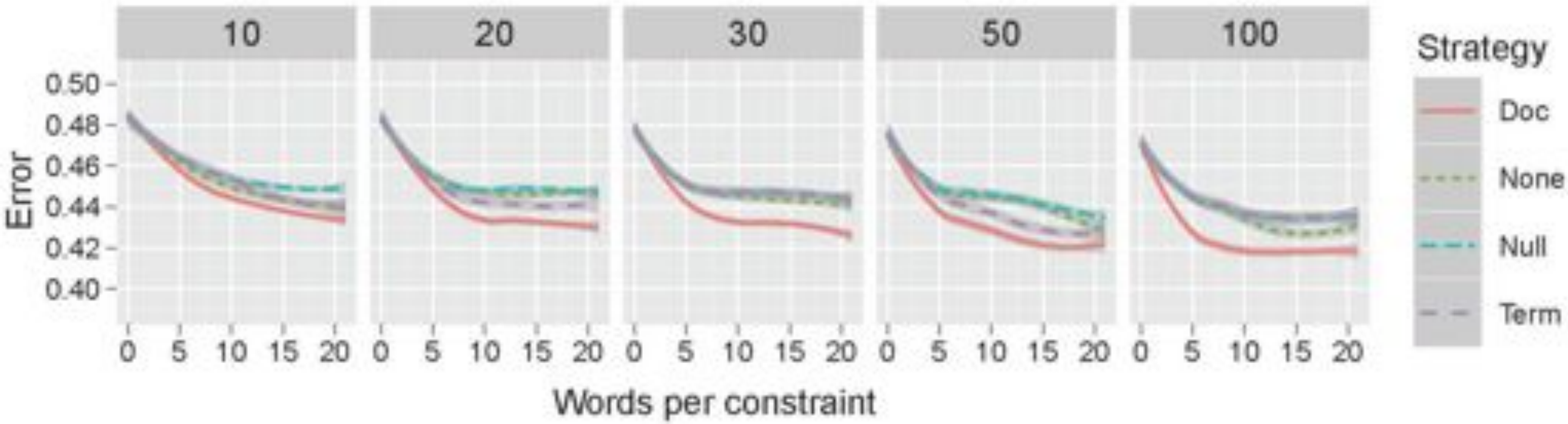
Topic	Before
2	new, york, city, state, mayor, budget, giuliani, council, cuomo, gov, plan, year, David, rudolph, dinkins, lead, need, governor, legislature, pataki
3	nuclear, arms, weapon, defense, treaty, missile, world, unite, yet, soviet, lead, would, control, korea, intelligence, test, nation, country, testing
4	president, bush, military, see, administration, clinton, american, force, reagan, war, unite, lead, economic, iraq, congress, america, iraqi, policy, aid, international,

Topic	After
2	new, york, city, state, mayor, budget, council, giuliani, gov, cuomo, year, rudolph, dink-ins, legislature, plan, david, governor, pataki, need, cut
3	nuclear, arms, weapon, treaty, defense, war, missile, may, come, test, american, world, would, need, lead, get, join, yet, clinton, nation
4	president, administration, bush, clinton, war, unite, force, reagan, american, america, make, nation, military, iraq, iraqi, troops, international, country, yesterday, plan

Simulating an interactive user

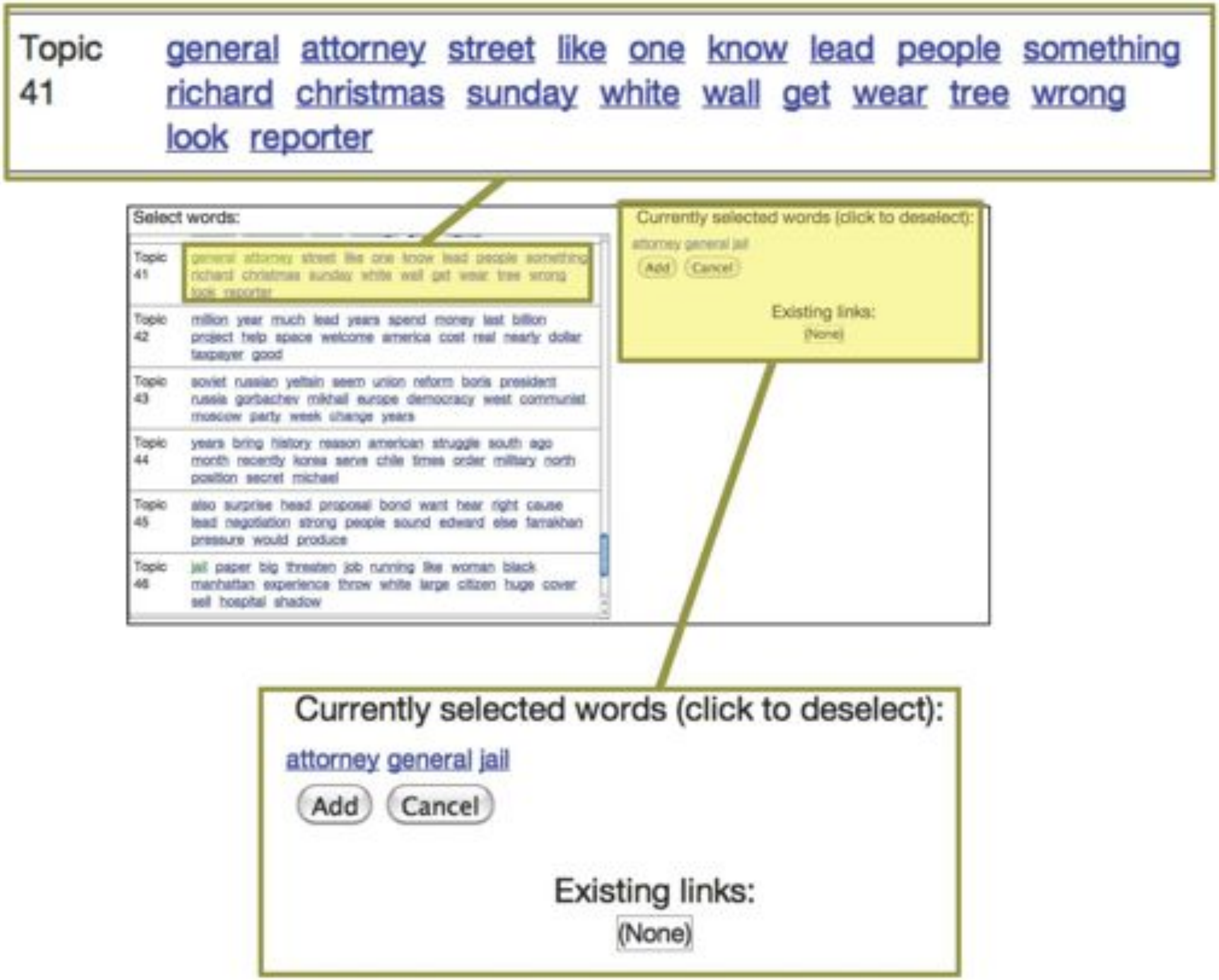
- Dataset: 20 News groups
- Constraints from feature selection on training data
  - soc.religion.christian: "catholic, scripture, resurrection, pope, sabbath, spiritual, pray, divine, doctrine"
  - 20 classes: 20 constraint sets, 21 words per constraint set
- Add them to the topic model as positive constraints
  - Add one word per class each time, 21 rounds in total
- Train classifier on training data
  - Use topic distribution of each doc as the feature
- Measure classification error rate of test data

Which strategy & how long to wait?



- Facet: number of iterations added per round
- Start with 100 iterations
- Null: no constraints, comparable iters
- “Doc” is best, run 30 or 50 iterations each round

Put humans in the loop



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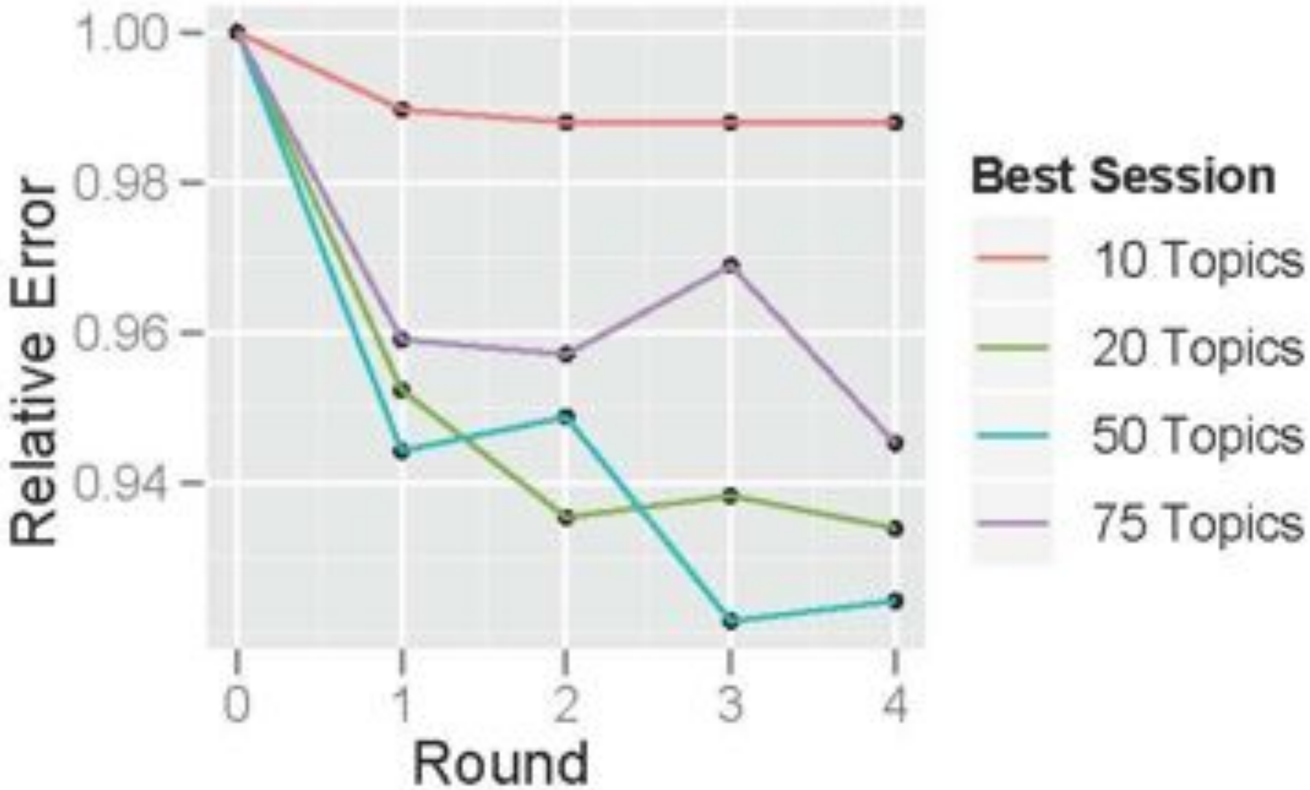

Put humans in the loop

- Some constraints users created
  - Inscrutable
    - better, people, right, take, things
    - fbi, let, says
  - Collocations
    - jesus, christ
    - solar, sun
    - even, number
    - book, list
  - Common instances (e.g. first names)
  - Soft constraint: mac, windows

Negative constraints

- NIH data(700 topics)
- Negative constraint: bladder – spinal_cord

Topic	Before	Topic	After
318	bladder, sci, spinal_cord, spinal_cord_injury, spinal, urinary, urinary_tract, urothelial, injury, motor, recovery, reflex, cervical, urothelium, functional_recovery	318	sci, spinal_cord, spinal_cord_injury, spinal, injury, recovery, motor, reflex, urothelial, injured, functional_recovery, plasticity, locomotor, cervical, locomotion

Conclusion

- An efficient way to refine and improve the topics discovered by topic models
- A paradigm for non-specialist consumers to refine models to better reflect their interests and needs
- Creating tools to do so
- We need users!

Future steps

- Speed up
- Suggesting constraints
- Incorporating other domain knowledge
- Incorporating interaction to other models

Thank you! Any questions?

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Constrained LDA

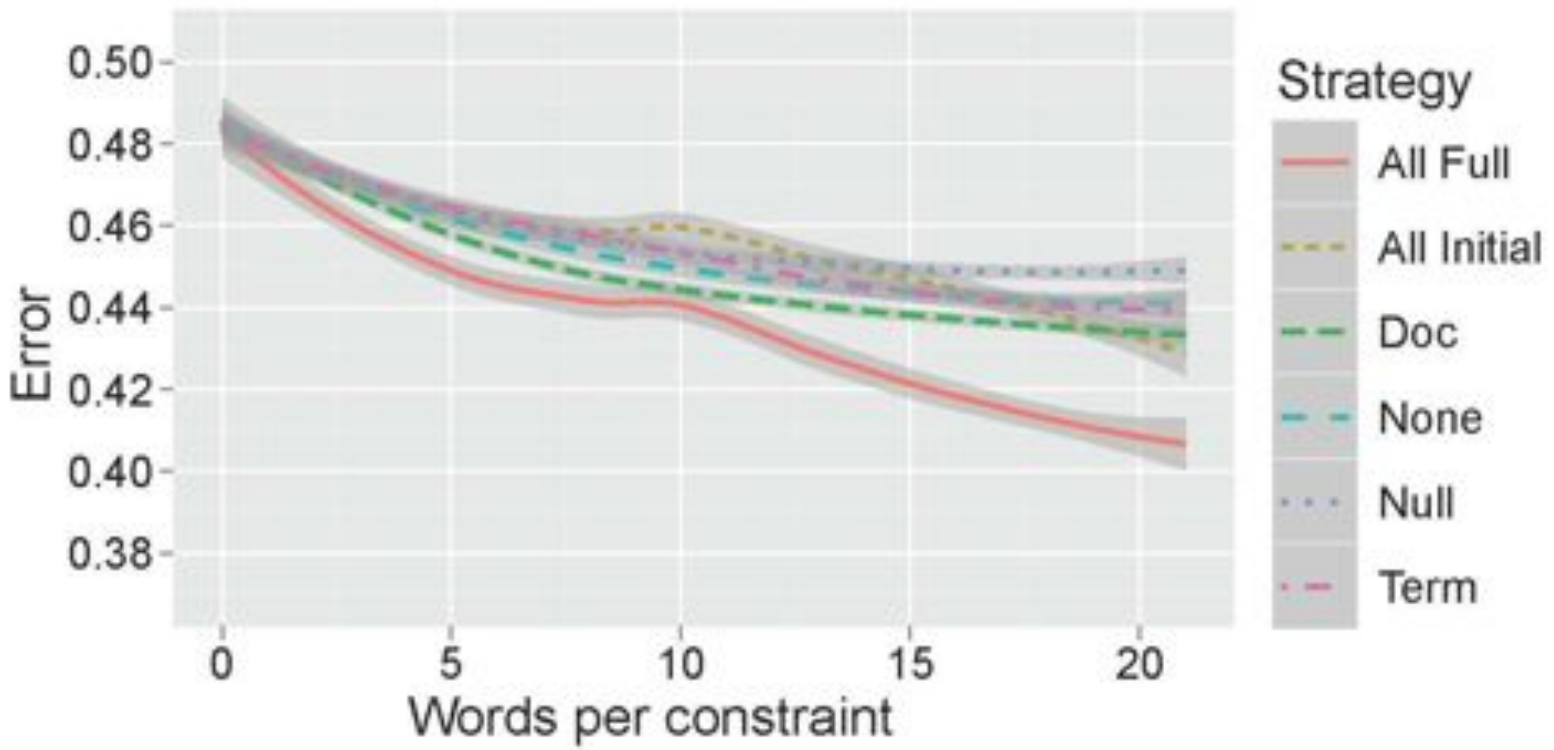
- Sampling equation

$$p(z_{d,n} = k | \mathbf{Z}_{-(d,n)}, \alpha, \beta, \eta)$$

$$\propto \begin{cases} \frac{T_{d,k}+\alpha}{T_{d,\cdot}+K\alpha} \frac{P_{k,w_{d,n}}+\beta}{P_{k,\cdot}+V\beta} & \text{if } \forall l, w_{d,n} \notin \Omega_l \\ \frac{T_{d,k}+\alpha}{T_{d,\cdot}+K\alpha} \frac{P_{k,l}+C_l\beta}{P_{k,\cdot}+V\beta} \frac{W_{k,l,w_{d,n}}+\eta}{W_{k,l,\cdot}+C_l\eta} & w_{d,n} \in \Omega_l \end{cases}$$

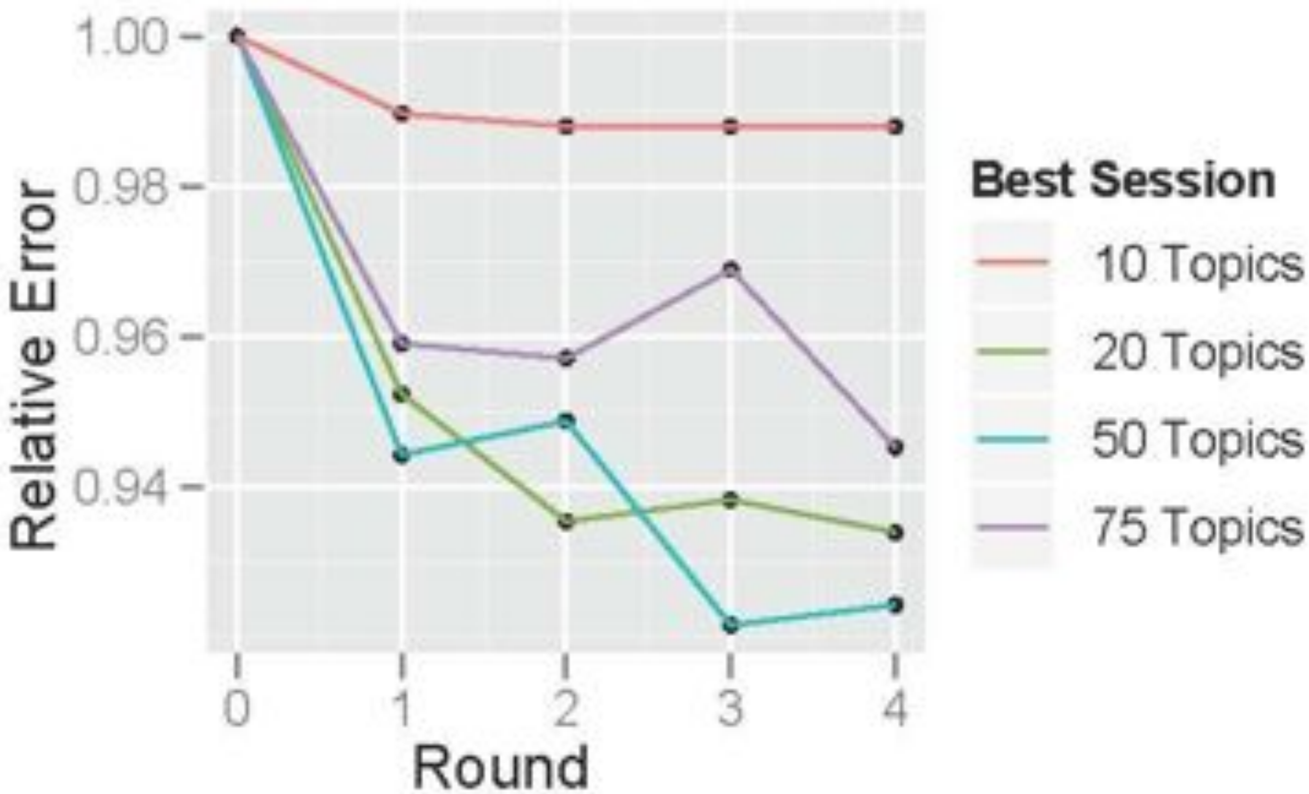
  - $P_{k,w_{d,n}}$ number of times the unconstrained word $w_{d,n}$ appears in topic k
  - $P_{k,l}$ number of times any word of constraint Ω_l appears in topic k
  - $W_{k,l,w_{d,n}}$ the number of times word $w_{d,n}$ appears in constraint Ω_l in topic k
  - V vocabulary size
  - C_l number of words in constraint Ω_l

Which strategy?



- All Full: all constraints are known, comparable iters
- All Initial: all constraints are known, 100 iters
- Null: no constraints, comparable iters

Put humans in the loop



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2. Jonathan Chang, Jordan Boyd-Graber, Chong Wang, Sean Gerrish, and David M. Blei. 2009. Reading tea leaves: How humans interpret topic models. In Neural Information Processing Systems.
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5. Jonathan Chang. 2010. Not-so-latent dirichlet allocation: Collapsed gibbs sampling using human judgments. In NAACL Workshop: Creating Speech and Language Data With Amazon’ss Mechanical Turk.