### HEADY: News Understanding Abstraction through Event Pattern Clustering

Enrique Alfonseca<sup>1</sup>, Daniele Pighin<sup>1</sup>, Guillermo Garrido<sup>2</sup>

ACL 2013 Sofia, Aug 6 2013

Google

<sup>1</sup>Google Inc., Zurich <sup>2</sup>UNED, Madrid, Spain

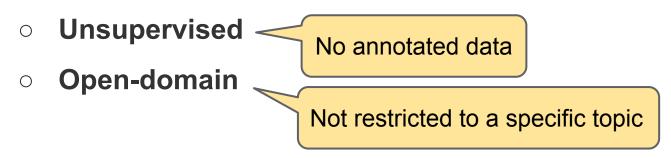
### From selection to generation

In most domains (e.g. celebrity news, sports) headlines are rarely objective, to-the-point descriptions:



### **Roadmap to abstractive headline generation**

1. Learn from data how the same event can be represented in text



- 2. Then, given a news stream:
  - Understand what events are reported in the news.
  - Generate **short**, **objective** headlines by specializing abstract event descriptions w.r.t. the evidence from the news.

## Agenda

- Learning an event model
- Headline generation
- Evaluation
- Conclusions

## Agenda

#### • Learning an event model

- Headline generation
- Evaluation
- Conclusions

### Event Relatedness in News Collections

#### **News Collections:**

Similar news published from various sources within a few days. 

#### Brazil newspapers look at protests' political impact

BBC News - 27 minutes ago

Brazil has this week seen its biggest protests since young people took to the streets in 1992 to demand the impeachment of President Fernando Collor de Mello, who was accused of corruption. The protests have been organised through social media, ...



euronews

IOC: 2016 Games will bring 'benefits' to Brazil

MSN Money - 8 minutes ago

IOC Confident Of Rio 2016 Despite Protests In Brazil

GamesBids.com - 10 minutes ago

AP PHOTOS: Protesters in Brazil Vow Further Action

ABC News - 11 minutes ago

Brazil Protest Update: Marches Spread to Small Cities, Police Prepare for Huge ...

Headlines & Global News - 16 minutes ago

### **Event Relatedness in News Collections**

#### Assumptions:

- The news in the same collection describe closely related events
- If the same set of entities is mentioned in titles and first sentences of the same NC:
  - => the event in which they are involved is likely to be the same

### **Patterns and news collections**

Anna Faris weds actor fiance in Bali ``The House Bunny'' star Anna Faris has married her fiance, actor Chris Pratt. 'House Bunny' star Anna Faris weds actor fiance Chris Pratt in Bali, Indonesia Chris Pratt and Anna Faris are seen during the

Malibu...

Anna Faris **ties the knot with** actor beau Anna Faris **marries** Chris Pratt in private ceremony

Anna Faris weds actor fiance in Bali ...

#### Jessica Alba marries Cash Warren

The 27-year-old actress quietly **wed** producer Cash Warren on Monday, her publicist, Brad Cafarelli, said Tuesday in an e-mail to The Associated Press.

Jessica Alba **ties the knot with** Cash Warren Jessica Alba **Marries** Boyfriend Cash Warren Jessica Alba Quietly **Marries** Fiance Jessica Alba and Cash Warren a hot family

[actor] weds [actor] [actor] has married [actor] [actor] and [actor] are seen [actor] ties the knot with [actor] [actor] marries [actor] [person] weds [person] [actor] marries [actor] [actor] ties the knot with [actor] [person] weds [person] [person] marries [person] [celebrity] weds [actor] [celebrity] and [actor] a hot family

### **Patterns and news collections**

Anna Faris weds actor fiance in Bali ``The House Bunny" star Anna Faris has married her fiance, actor Chris Pratt. 'House Bunny' star Anna Faris weds actor fiance Chris Pratt in Bali, Indonesia Chris Pratt and Anna Faris are seen during the

Malibu...

Anna Faris **ties the knot with** actor beau Anna Faris **marries** Chris Pratt in private ceremony

Anna Faris weds actor fiance in Bali ...

#### Jessica Alba marries Cash Warren

The 27-year-old actress quietly **wed** producer Cash Warren on Monday, her publicist, Brad Cafarelli, said Tuesday in an e-mail to The Associated Press.

Jessica Alba **ties the knot with** Cash Warren Jessica Alba **Marries** Boyfriend Cash Warren Jessica Alba Quietly **Marries** Fiance Jessica Alba and Cash Warren a hot family

[actor] weds [actor] [actor] has married [actor] [actor] and [actor] are seen [actor] ties the knot with [actor] [actor] marries [actor] [person] weds [person] [actor] marries [actor] [actor] ties the knot with [actor] [person] weds [person] [person] marries [person] [celebrity] weds [actor] [celebrity] and [actor] a hot family

## Learning abstract representations of events (I)

**Input**: A corpus **S** of dependency parsed, entity-disambiguated news collections.

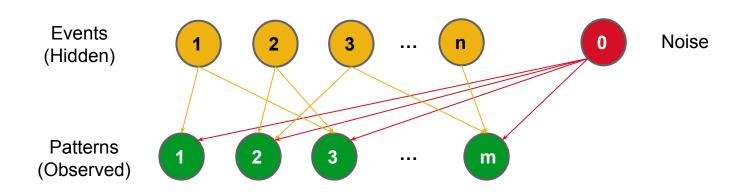
- 1. For each news collection C in S:
  - a. Select the set of the most important entities *E* in *C*.
  - b. For each document *D* in *C*:
    - i. For each combination *E*' of the elements of *E*:
      - 1. Extract from the title and first sentence of *D* a *syntactic pattern*

encoding the relation among the entities E'.

[ continue ...]

### Learning abstract representations of events (II)

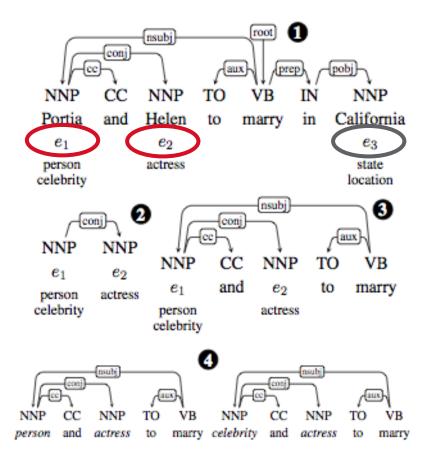
- [... continued]
- 2. Group the patterns on a per News Collection, per entity-set basis.
- Train a Noisy-OR network to learn the hidden events (event types) that generate the observed patterns using pattern groups to bootstrap EM process.



## Pattern extraction in detail

- 1. Select target entity mentions.
- 2. Extract Minimum Spanning Tree.
- 3. Enforce grammaticality (heuristics).
- Generate pattern instances by combining class assignments.

We treat patterns as atomic tokens.



## **Disambiguating entities (II)**

- Entities of the same type might be confused in the patterns.
  - OK for **symmetric** relations, e.g.:

*Tom Cruise married Katie Holmes* => [celebrity] married [celebrity]

• An issue for **asymmetric** ones, e.g.:

*Tom Cruise killed Katie Holmes* => [celebrity] killed [celebrity]

- Solution: add *alphabetical offsets* to distinguish entities:
  - Tom Cruise married Katie Holmes => [celebrity-2] married [celebrity-1]
  - *Katie Holmes married Tom Cruise* => [celebrity-1] married [celebrity-2]
  - *Tom Cruise killed Katie Holmes* => [celebrity-2] killed [celebrity-1]
  - Katie Holmes killed Tom Cruise => [celebrity-1] killed [celebrity-2]

### **Co-occurrence and equivalence**

• If patterns co-occur within the same news collections, we assume that the two patterns are equivalent.

#### Symmetric relations

[person-0], [person-1] divorce[business-0] and [business-1] join forces[person-1], [person-0] divorce[business-1] and [business-0] join forces

#### **Argument rotation**

[team-0] hires [person-1] as coach[team-0] acquires [athlete-1] from [team-2][person-1] new coach of [team-0][team-2] sells [athlete-1] to [team-0]

#### Syntactic alternation

[band-0] hires [person-1]

[person-1] hired by [band-0]

[person-0] gave a ring to [person-1]

[person-0] gave [person-1] a ring

## A glimpse inside the model

### Syntactic alternation and argument movement

[professional\_sports\_teams]2 replace [ice\_hockey\_coaches]1 with [ice\_hockey\_coaches]0 [professional\_sports\_teams]2 fire [ice\_hockey\_coaches]1 , hire [ice\_hockey\_coaches]0 [professional\_sports\_teams]2 fire [coaches]1 , replace him with [ice\_hockey\_coaches]0 [ice\_hockey\_teams]2 fire [professional\_ice\_hockey\_coaches]1 hire [ice\_hockey\_coaches]0 [professional\_sports\_teams]2 hire [coaches]0 after firing [ice\_hockey\_coaches]1

#### [colleges-universities]1 introduces [coaches]0

[coaches]0 was introduced as basketball coach at [colleges-universities]1 [coaches]0 introduced as [colleges-universities]1 's coach [professional\_basketball\_players]0 introduced as [colleges-universities]1 's coach [educational\_institution\_campus]1 introduces [professional\_basketball\_players]0 [colleges-universities]1 introduces [professional\_basketball\_players]0 [basketball\_players]0 introduced as [private\_universities]1 's coach [basketball\_players]0 was introduced as basketball coach at [private\_universities]1

### A glimpse inside the model

Syntactic alternation and argument movement

[sports\_teams]0 dismiss [soccer\_players]1 [soccer\_teams]0 dismiss [soccer\_midfielders]1 [sports\_teams]0 axe falls on [soccer\_midfielders]1 [sports\_teams]0 fires [soccer\_players]1 [sports\_teams]0 axe falls on [soccer\_players]1 [sports\_teams]0 fires [soccer\_midfielders]1 [soccer\_players]1 sacked by [sports\_teams]0

> [athletes]1 replaces injured [athletes]0 [people]1 replaces injured [people]0 [people]1 replaces [athletes]0 [people]1 replaces [people]0 [people]1 steps for [people]0 injured [men]0 replaced by [men]1 injured [people]0 replaced by [people]1

### A glimpse inside the model Context-based verb disambiguation

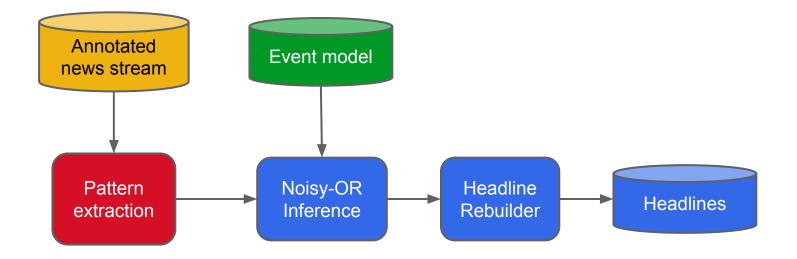
the [armed\_forces]0 awarded [aerospace\_businesses]1 a contract
the [armed\_forces]0 awarded [arms\_manufacturers\_businesses]1
[aerospace\_businesses]1 wins [armed\_forces]0 contract
the [armed\_forces]0 has contracted [aerospace\_businesses]1
the [armed\_forces]0 selected [aerospace\_engineering\_businesses]1
that [arms\_manufacturers\_businesses]1 received a contract from the [armed\_forces]0

[organization\_leaders]0 wins [award\_categories]1 [entrepreneurs]0 awarded laward\_categories]1 [organization\_leaders]0 receives [award\_categories]1 [politicians]0 to receive [award\_categories]1 [businesspeople]0 to get [literature\_subjects]1 [organization\_leaders]0 gets [literature\_subjects]1

## Agenda

- Learning an event model
- Headline generation
- Evaluation
- Conclusions

### **Abstractive headline generation**



### **Headline examples**

#### Snippets

Actress Alyssa Milano to wed Hollywood agent

Publicists for Milano said Tuesday that the actress accepted a marriage proposal on Dec. 18

from David Bugliari, an agent at Creative Artists Agency.

Actress Alyssa Milano to wed Hollywood agent

Alyssa Milano is engaged to marry a Hollywood agent.

Alyssa Milano To Marry Hollywood Agent

The information you provide will be used only to send the requested e-mail and will n used to send any other e-mail communications.

Actress Alyssa Milano to wed Hollywood agent LOS ANGELES --

#### PHOTO: ALYSSA MILANO ENGAGED TO MARRY AGENT

Bugliari proposed to the former Charmed star just before Christmas, according to Usmagazine.com.

#### Alyssa Milano Ready To Walk The Aisle Again!

Los Angeles 08/01/2009- Looks like the Charmed actress has floored someone again with her magical charm.

#### Actress Alyssa Milano to wed Hollywood agent

AP Breaking News Video Publicists for Milano said Tuesday that the actress accepted a marriage proposal on Dec. 18 from David Bugliari, an agent at Creative Artists Agency.

Alyssa Milano is engaged to David Bugliari Alyssa Milano is set to marry David Bugliari Alyssa Milano , David Bugliari engaged Alyssa Milano to marry David Bugliari Alyssa Milano engaged to David Bugliari

## Agenda

- Learning an event model
- Headline generation
- Evaluation
- Conclusions



Can we produce abstractive (**A**) headlines comparable with extractive (**E**) ones?

Compared against 5 baselines:

- TopicSum [Haghighi and Vanderwende, 2009] (E)
- Most frequent headline (E)
- Latest headline (E)
- Most frequent pattern (Pattern extraction w/o inference) (E)
- Multi-Sentence Compression (MSC) [Filippova, 2010] (A)

Two evaluations:

- Automatic: ROUGE [Lin, 2004] over golden references
  - Selected 50 never-seen before collections for which all systems could generate an output:
    - 5 annotators produced 4-5 headlines for each NC
    - Instructed to write informative, objective headlines
- Manual: *Readability & Informativeness* on 5-point Likert scale:
  - 3 human raters for each headline [template].
  - Intra-class correlation (0.95 confidence interval):
    - Readability: Good; Informativeness: Moderate

### **Evaluation of headline generation (Heady, ACL 2013)**

	Rouge-1	Rouge-2	Rouge-SU4	Read.	Inform.
Heady (A)	0.3565	0.1903	0.1966	4.28	3.75
Most frequent pattern	0.3560	0.1864	0.1959	3.95	3.82
TopicSum	0.3594	0.1821	0.1935	4.86	4.63
MSC (A)	0.3470	0.1765	0.1855	3.00	3.05
Most frequent headline	0.3177	0.1401	0.1668	4.61	4.43
Latest headline	0.2814	0.1191	0.1425	4.55	4.00

- Different rankings according to the two evaluations.
  - ROUGE not good at distinguishing Human vs. Machine generated.
- Heady better than MSC (0.95 confidence interval) on all metrics:
  - It fills half of the gap between abstractive and extractive state of the art.

	Rouge-1	Rouge-2	Rouge-SU4	Read.	Inform.
Heady (A)	0.3565	0.1903	0.1966	4.28	3.75
Most frequent pattern	0.3560	0.1864	0.1959	3.95	3.82
TopicSum	0.3594	0.1821	0.1935	4.86	4.63
MSC (A)	0.3470	0.1765	0.1855	3.00	3.05
Most frequent headline	0.3177	0.1401	0.1668	4.61	4.43
Latest headline	0.2814	0.1191	0.1425	4.55	4.00

- Not surprisingly, extractive methods are evaluated very positively.
- No explicit question about objectivity, raters might be biased towards catchy headlines.

	Rouge-1	Rouge-2	Rouge-SU4	Read.	Inform.
Heady (A)	0.3565	0.1903	0.1966	4.28	3.75
Most frequent pattern	0.3560	0.1864	0.1959	3.95	3.82
TopicSum	0.3594	0.1821	0.1935	4.86	4.63
MSC (A)	0.3470	0.1765	0.1855	3.00	3.05
Most frequent headline	0.3177	0.1401	0.1668	4.61	4.43
Latest headline	0.2814	0.1191	0.1425	4.55	4.00

- TopicSum significantly better than:
  - All others for readability;
  - All but Most Frequent Headline for informativeness.

	Rouge-1	Rouge-2	Rouge-SU4	Read.	Inform.
Heady (A)	0.3565	0.1903	0.1966	4.28	3.75
Most frequent pattern	0.3560	0.1864	0.1959	3.95	3.82
TopicSum	0.3594	0.1821	0.1935	4.86	4.63
MSC (A)	0.3470	0.1765	0.1855	3.00	3.05
Most frequent headline	0.3177	0.1401	0.1668	4.61	4.43
Latest headline	0.2814	0.1191	0.1425	4.55	4.00

- Most frequent pattern and Heady comparable across all metrics.
- Heady is slightly better (not significantly) than MFP for readability
   => Abstraction seems to compensate for pattern extraction errors.

## Agenda

- Learning an event model
- Headline generation
- Evaluation
- Conclusions

### Conclusions

- Unsupervised, open-domain, simple framework for event learning
- Captures relevant linguistic phenomena:
  - Syntactic alternations
  - Argument movement
  - Symmetric vs. Asymmetric relations
- Use it for abstractive headline generation:
  - Significant improvement over abstractive state of the art.
  - Halved the gap w.r.t. human generated headlines (extractive).

### **Directions for improvement**

• Heuristics can fail to generate well-formed sentences, e.g.:

Thanks!

[person] [person] moving to [sport team]

- Noise in the event model, e.g., "[person] gets [person]"
- Ungrammatical output for headline generation
- Automatically learn pattern-building rules from data
- Applications to Knowledge Base population
- Headline personalization (e.g., reading level, stylistic preferences)

### **Headline examples**

#### Snippets

#### Will and Jada Pinkett Smith: Splitting Up?

It's no secret that Hollywood takes a serious toll on marriages, and it seems Will Smith and his wife Jada Pinkett Smith may be headed for Splitsville.

#### Will and Jada Pinkett Smith Supposed Split Update

As an update to the GossipCenter story on Will and Jada Pinkett Smith's marital woes, the celebrity couple hasn't made an official split just yet.

#### Will & Jada Pinkett Smith: We're Not Breaking Up!

Quickly shooting down any speculation of a split, Will and Jada Pinkett Smith issued a statement regarding a tabloid claim of a divorce in the works.

#### Will & Jada Smith: Happily In Love in Malibu

Putting those pesky divorce rumors to rest once and for all, Will Smith and Jada Pinkett Smith were spotted side-by-side while out in Malibu, CA on Wednesday.

#### Smith and Pinkett Smith not separating

Will Smith has dismissed reports suggesting he and wife Jada Pinkett Smith are on the verge of splitting up, insisting their marriage is ``intact."

#### Will & Jada Pinkett Smith Slam Marriage Split Rumors Hopeless romantics need not fret.

Why Will & Jada's Union Matters

I admit it, I wanted to know whether Will & Jada were on their way to a divorce.

#### Will and Jada Smith deny breakup reports

After a day of false speculation, Will and Jada Pinkett Smith issued a statement saying their marriage is not in trouble and they are not separating.

#### Will Smith and Jada Pinkett-Smith separation reports UPDATE

radaronline is reporting they spoke with a family member who is denying the reports of Will Smith and Jada Pinkett Smith's alleged separation from InTouch Weekly.

#### Abstracted headlines

#### Entities: /m/0147dk /m/01j7z7 Relevance: 1.00000

Will Smith denies split with Jada Pinkett Smith Will Smith denies split from Jada Pinkett Smith Will Smith denies Jada Pinkett Smith split Will Smith , Jada Pinkett Smith split Will Smith splits up with Jada Pinkett Smith Will Smith split from Jada Pinkett Smith Will Smith splits from Jada Pinkett Smith Will Smith splits from Jada Pinkett Smith Jada Pinkett Smith splits with Will Smith Jada Pinkett Smith splits from Will Smith Will Smith denies Jada Pinkett Smith Will Smith dumped Jada Pinkett Smith Will Smith dumped Jada Pinkett Smith Will Smith dumped Jada Pinkett Smith

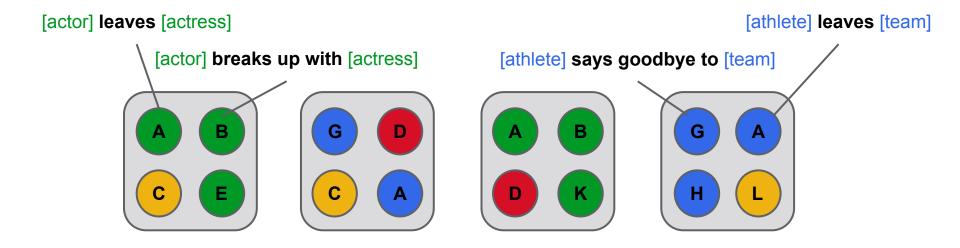
### **Event-relatedness in Google News Clusters**

 Observe the same relation (pattern) among the same entity types across different news collections to learn alternative ways of expressing the same event.



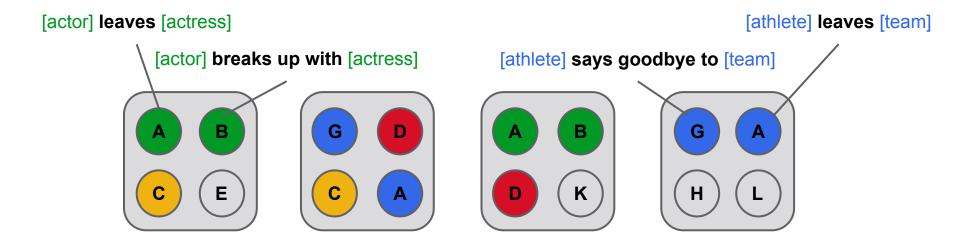
### **Event-relatedness in Google News Clusters**

 Observe the same relation (pattern) among the same entity types across different news collections to learn alternative ways of expressing the same event.



### **Event-relatedness in Google News Clusters**

 Observe the same relation (pattern) among the same entity types across different news collections to learn alternative ways of expressing the same event.



## Agenda

- Learning an event model
- Headline generation
- Directions for improvement
- Conclusions

#### Google Knowledge Graph: Map the universe of *things*, not just webpages.





**Baseball teams** 



#### Museums















**Movie Directors** 



#### Music groups



#### Islands



#### Politicians



#### Music albums



#### **Roller coasters**



Countries



#### Theater actors



#### **Cricket teams**



#### Spacecraft



#### **TV Actors**



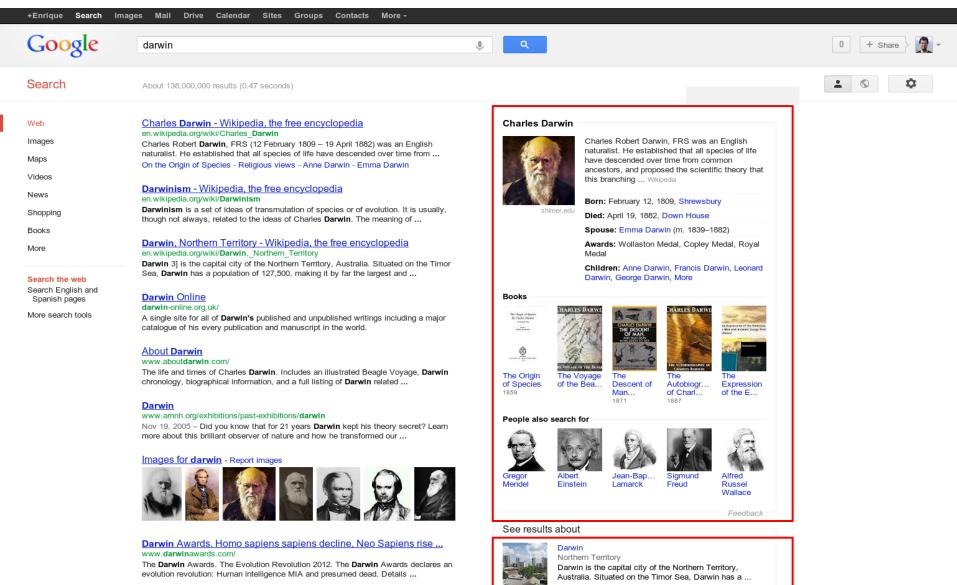
#### Lakes



The Google Knowledge Graph: Over the past two years. Google has created a database of structured knowledge.

500 million people, places and things3.5 billion defining attributes and connections

#### Information shown in web search



City of Darwin

#### BBC - History - Charles Darwin

### **Event inference using the Noisy-OR Bayesian Net**

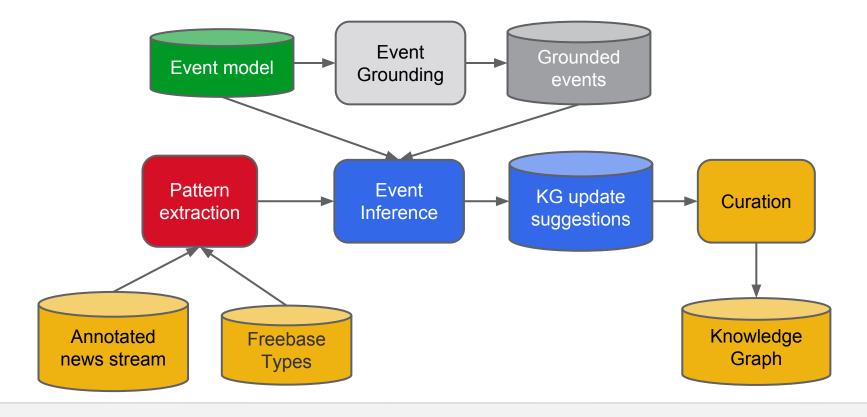
At test time, given a news collection *C* we want to understand what events are activated by the news collection.

- 1. Collect syntactic patterns *P* from *C*, as for training.
- Invoke noisy-OR inference: find the clusters that better explain the observed patterns P
  - approximated inference
- 3. The pattern cluster that better explains the news collection may indicate that some update is needed in the knowledge graph, e.g.
  - Weddings: add a spouse relation
  - Job transfers: add an employed-by relation

### **Event clusters for Knowledge Graph updates**

A very useful application of event clusters:

- Monitor news streams for activated events.
- Semi-automatic updates the Knowledge Graph



## **Evaluation of event clusters for KG updates (II)**

- Informal evaluation: manually annotated 40 clusters corresponding to 5 event types.
- Two weeks of observation, triggered 90 times.

Event type	Precision
Joining the cast of a production	0.65
Organizational staff changes	0.78
People dying / being killed	0.94
People planning to get married	0.67
People splitting / divorcing	0.50

- No results for recall yet (but we know we have to increase it)
- Ongoing work on automatically grounding the pattern clusters.