-- CS341 info session is on Thu 3/12 6pm in Gates415
-- Final exam logistics
-- Please fill out course evaluation forms (THANKS!!!)

Optimizing Submodular Functions

CS246: Mining Massive Datasets
Jure Leskovec, Stanford University
http://cs246.stanford.edu

Announcement: Final Exam Logistics

Final: At Stanford

- Alternate final: Mon 3/16 7:00-10:00pm in Bishop Auditorium (Lathrop Library)
  - Register at: http://goo.gl/forms/5505oC0Y94
- Final: Fri 3/20 12:15-3:15pm
  NVidia (Lastname starting with A-M)
  Hewlett200 (Lastname starting with N-Z)
  - See http://campus-map.stanford.edu
  - Practice finals + Gradiance quizzes will be on Piazza
  - Open book, open computer, no internet
- SCPD students can take the exam at Stanford!

Final: SCPD Students

- **Exam protocol for SCPD students:**
  - On **Monday 3/16** your exam proctor will receive the PDF of the final exam from SCPD
  - **If you take the exam at Stanford:**
    - Ask the exam monitor to delete the SCPD email
  - **If you don't take the exam at Stanford:**
    - Arrange a **3h** slot with your exam monitor
    - You can take the exam **anytime** but return it in time
    - **Email exam PDF to cs246.mmds@gmail.com by Thursday 3/19 11:59pm Pacific time**

Announcement: CS341: Project in Mining Massive Datasets

CS341

- **Data mining research project on real data**
  - Groups of 3 students
  - **We provide interesting data, computing resources (Amazon EC2) and mentoring**
  - **You provide project ideas**
  - Class meets once a week + individual group mentoring

Information session:
Thursday 3/12 6:00pm in Gates 415
(there will be pizza!)

CS341: Schedule

- **Thu 3/12: Info session**
  - We will introduce datasets, problems, ideas
- **Students form groups and project proposals**
- **Mon 3/23: Project proposals are due**
- **We evaluate the proposals**
- **Mon 3/30: Admission results**
  - **10 to 15 groups/projects will be admitted**
- **Mon 5/4, Wed 5/6: Midterm presentations**
- **Thu 6/11: Presentations, poster session**

More info: http://cs341.stanford.edu

Optimizing Submodular Functions

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Recommendations: Diversity

- Redundancy leads to a bad user experience

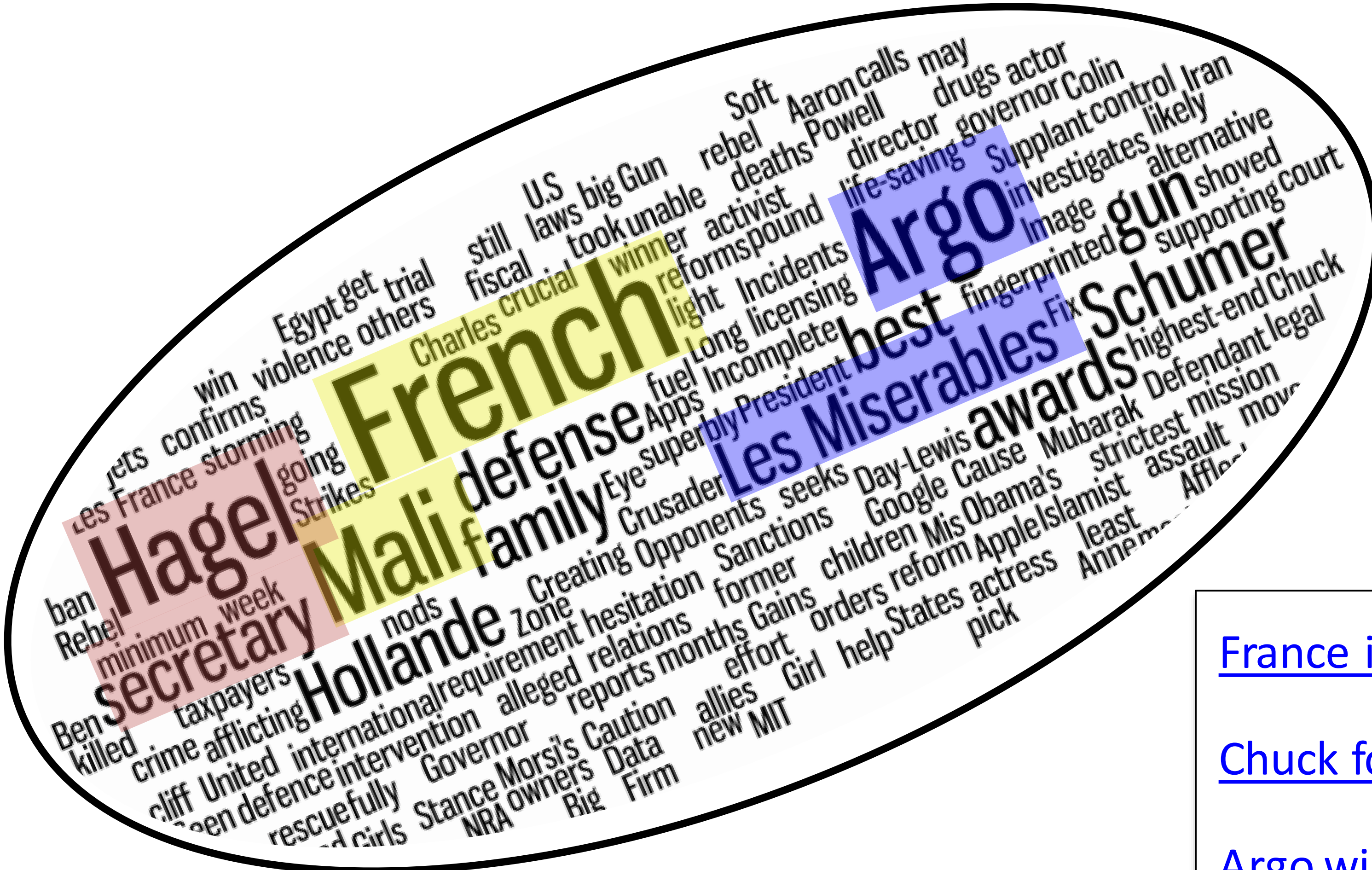
Obama Calls for Broad Action on Guns

Obama unveils 23 executive actions, calls for assault weapons ban

Obama seeks assault weapons ban, background checks on all gun sales

  - Uncertainty around information need => don't put all eggs in one basket
- How do we optimize for diversity directly?

Covering the day's news



France intervenes

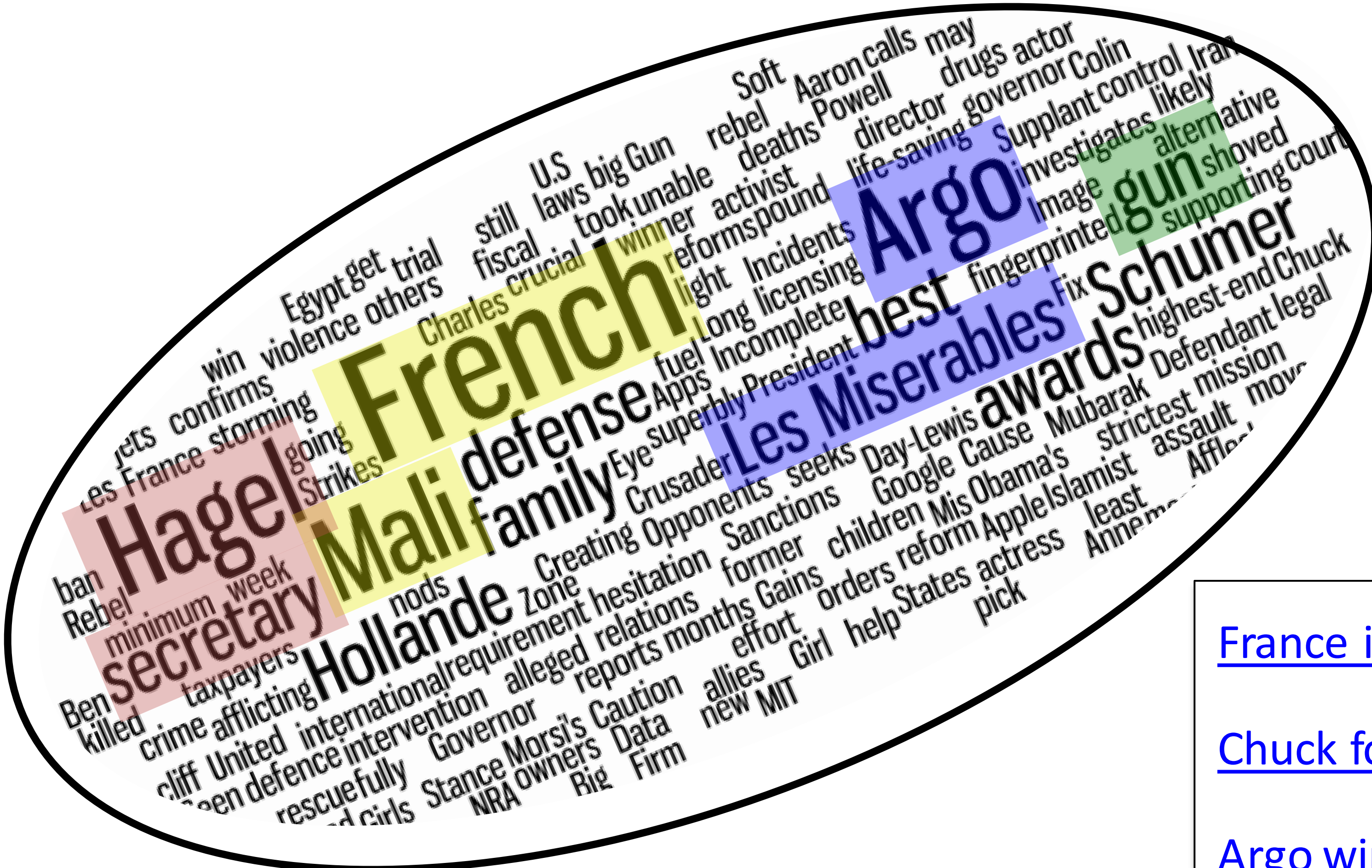
Chuck for Defense

Argo wins big

Hagel expects fight

Monday, January 14, 2013

Covering the day's news



[France intervenes]

[Chuck for Defense]

[Argo wins big]

[New gun proposals]

Monday, January 14, 2013

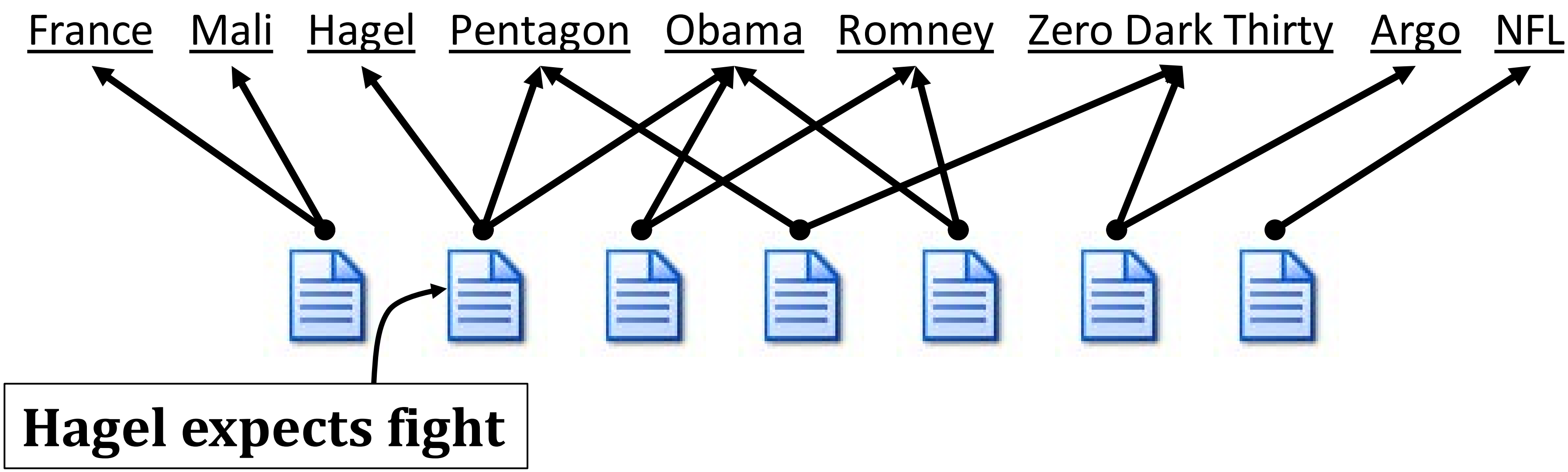
Encode Diversity as Coverage

- **Idea:** Encode diversity as coverage problem
- **Example:** Word cloud of news for a single day
  - Want to select articles so that most words are "covered"

Diversity as Coverage

What is being covered?

- **Q: What is being covered?**
- **A: Concepts** (In our case: Named entities)



- **Q: Who is doing the covering?**
- **A: Documents**

Simple Abstract Model

- **Suppose we are given a set of documents V**
  - Each document **d** covers a set X_d of words/topics/named entities **W**
- **For each set of documents *A* we define**

$$F(A) = \left| \bigcup_{d \in A} X_d \right|$$

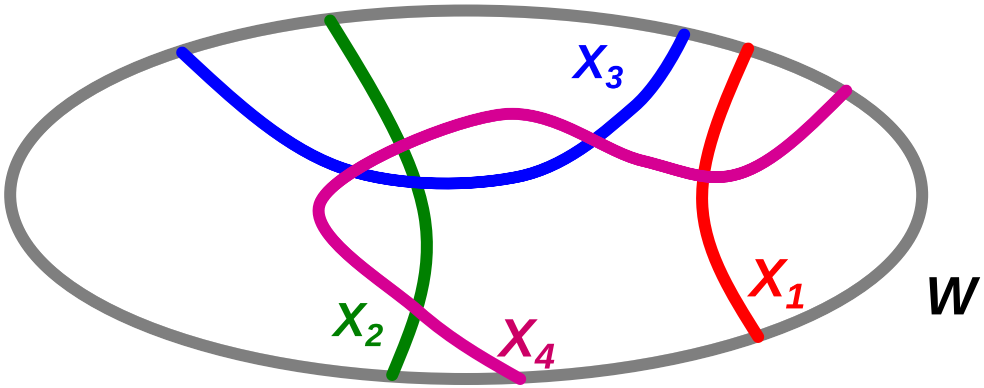
- **Goal: We want to**

$$\max_{|A| \leq k} F(A)$$

- **Note: *F(A)* is a set function:** $F(A)\colon \textbf{Sets} \to \mathbb{N}$

Maximum Coverage Problem

- **Given universe of elements $W = \{w_1, \dots, w_n\}$ and sets $X_1, \dots, X_m \subseteq W$**



- **Goal: Find *k* sets X_i that cover the most of *W***
  - **More precisely: Find *k* sets X_i whose size of the union is the largest**
  - **Bad news:** A known NP-complete problem

Simple Greedy Heuristic

Simple Heuristic: Greedy Algorithm:

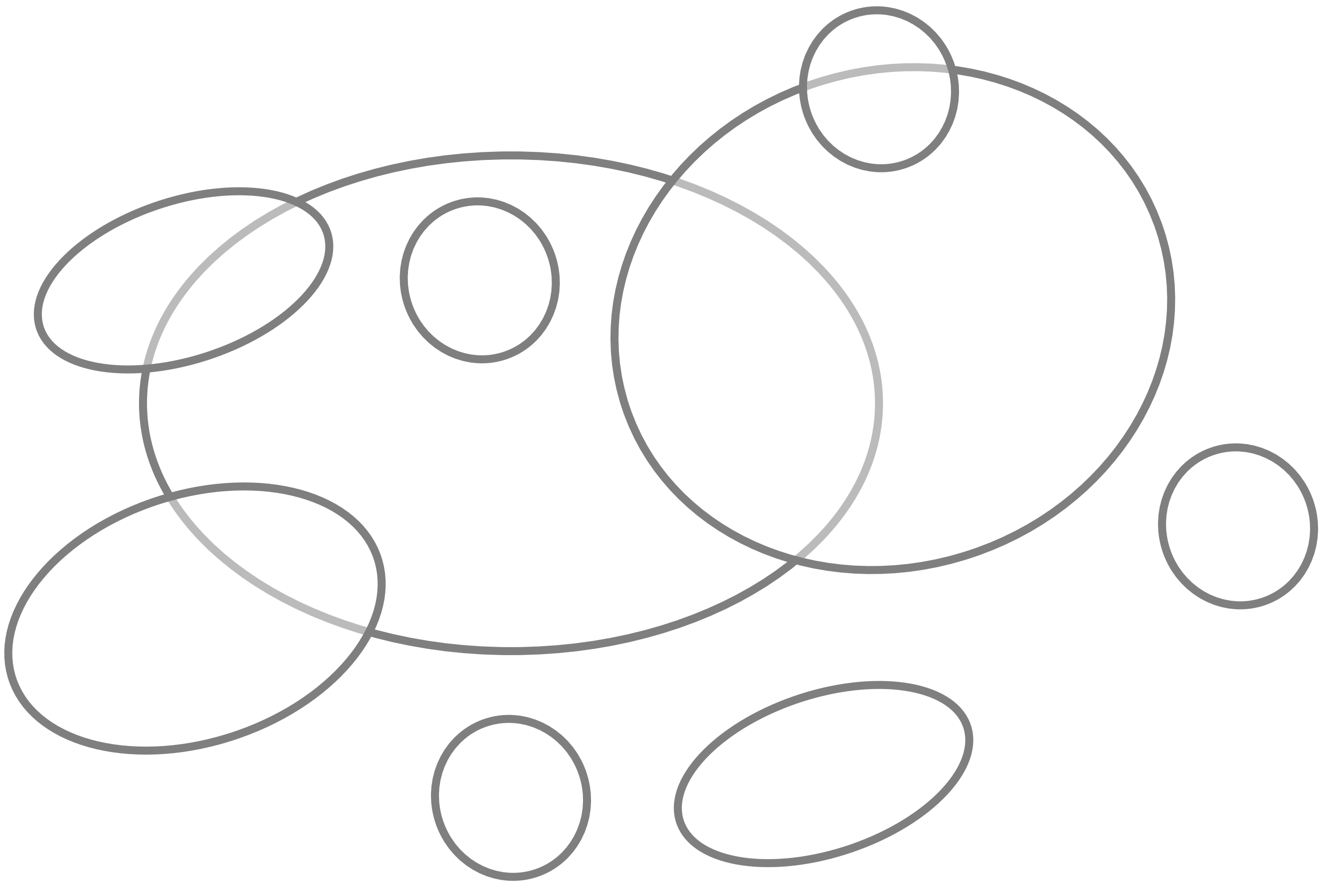
- Start with $A_0 = \{\ \}$
- For $i = 1 \dots k$
  - Take set d that $\max F(A_{i-1} \cup \{d\})$
  - Let $A_i = A_{i-1} \cup \{d\}$

$$F(A) = \left| \bigcup_{d \in A} X_d \right|$$

- **Example:**
  - Eval. $F(\{d_1\}), \dots, F(\{d_m\})$, pick best (say d_1)
  - Eval. $F(\{d_1\} \cup \{d_2\}), \dots, F(\{d_1\} \cup \{d_m\})$, pick best (say d_2)
  - Eval. $F(\{d_1, d_2\} \cup \{d_3\}), \dots, F(\{d_1, d_2\} \cup \{d_m\})$, pick best
  - And so on…

Simple Greedy Heuristic

- **Goal: Maximize the covered area**



Simple Greedy Heuristic

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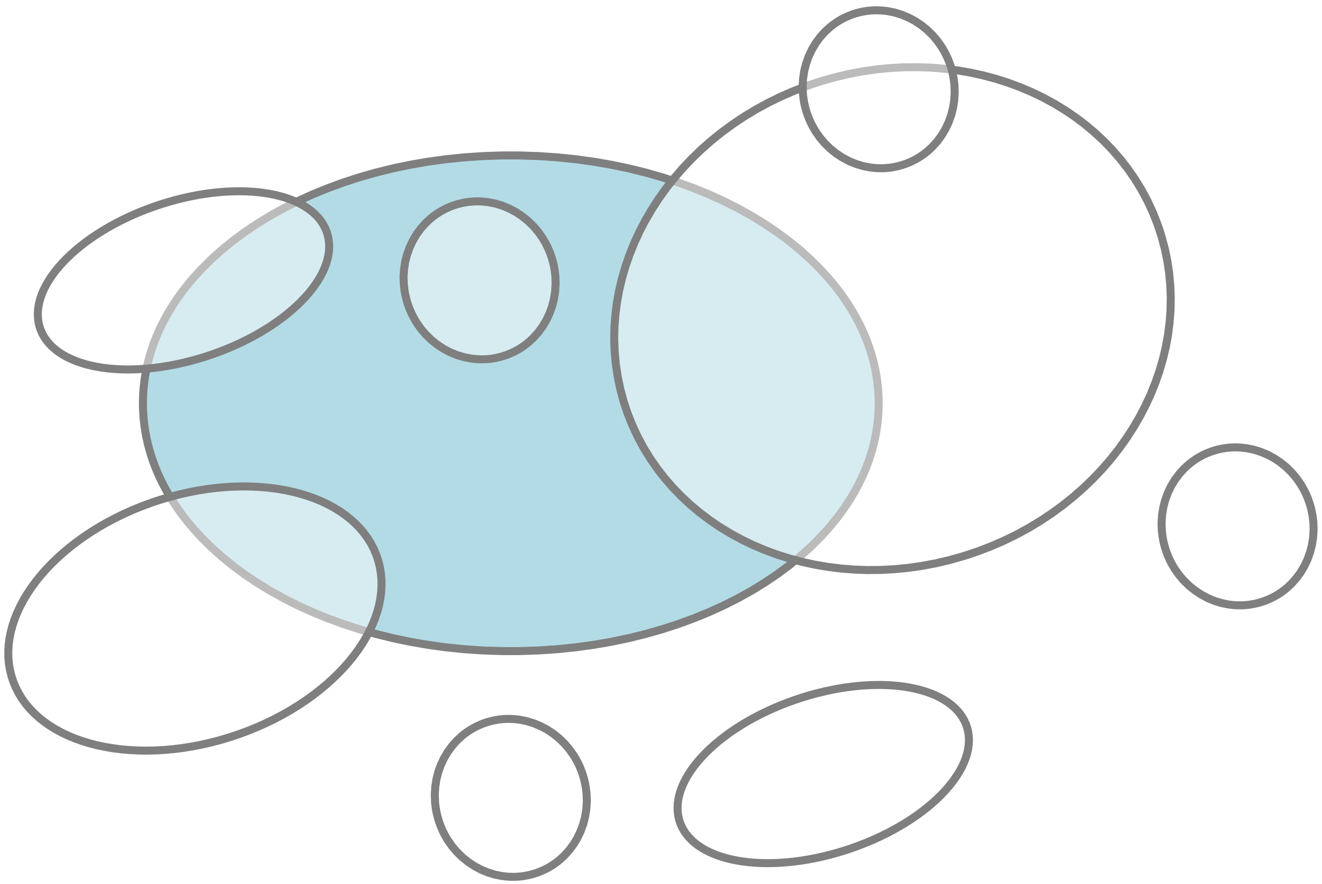

Simple Greedy Heuristic

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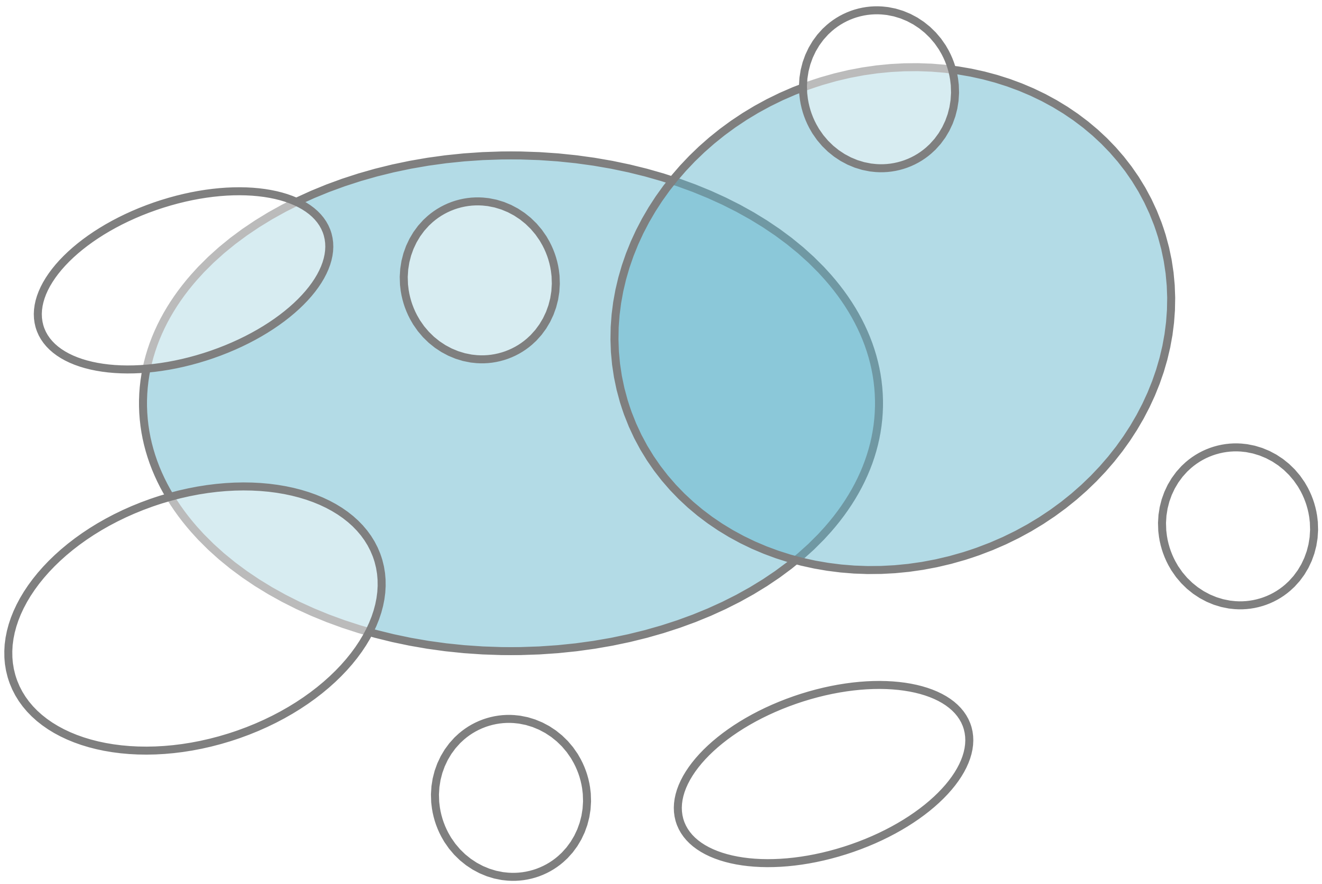

Simple Greedy Heuristic

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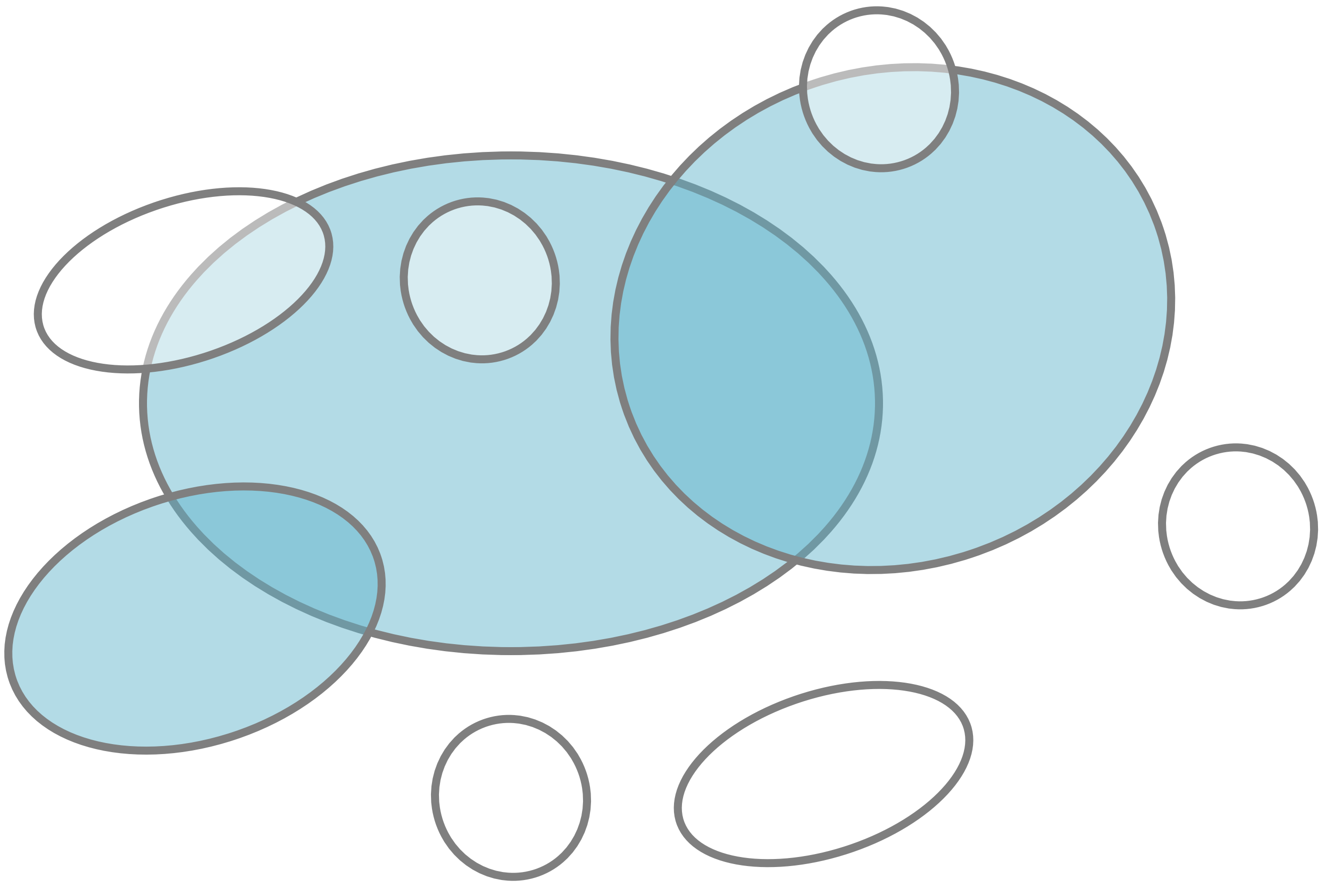
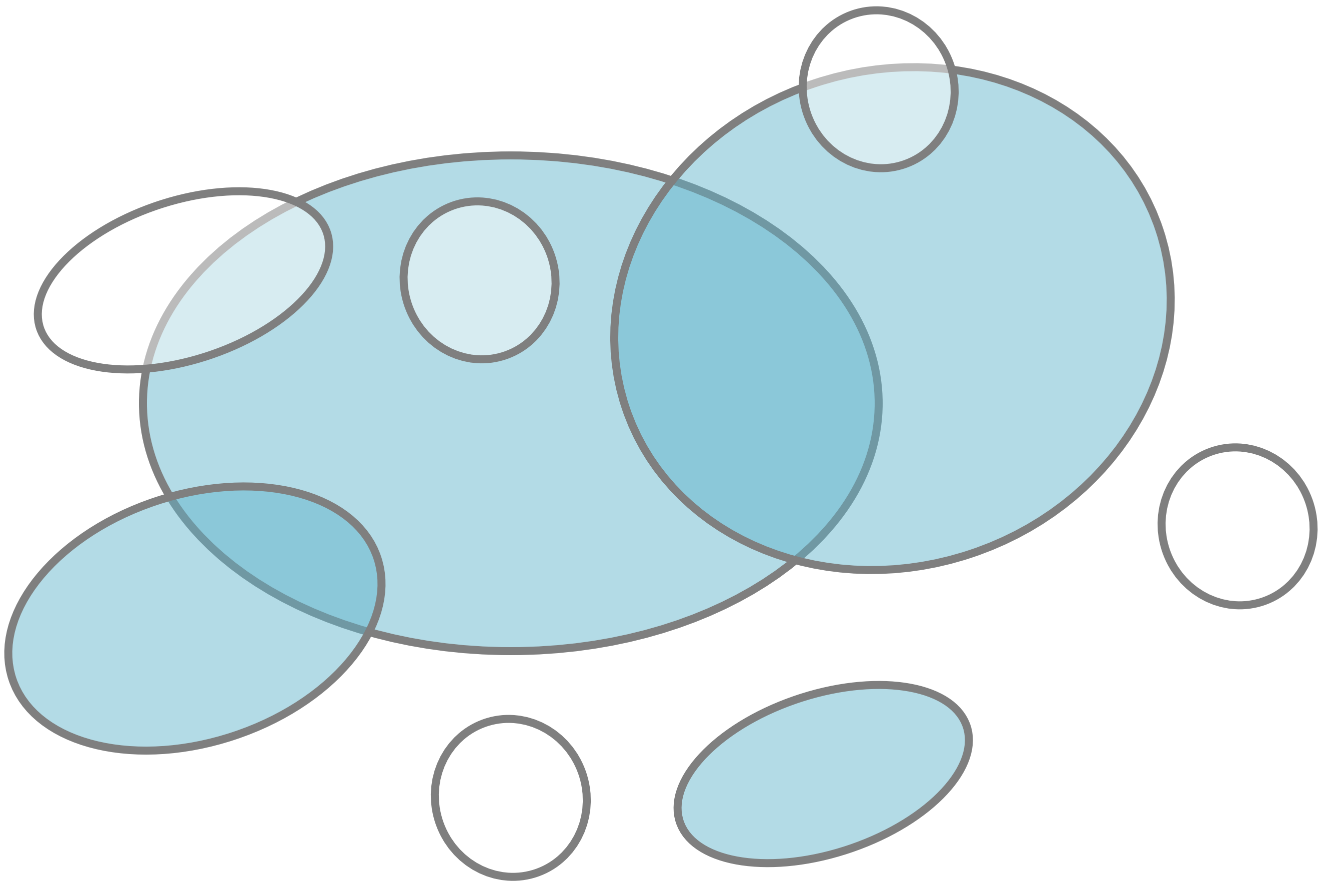
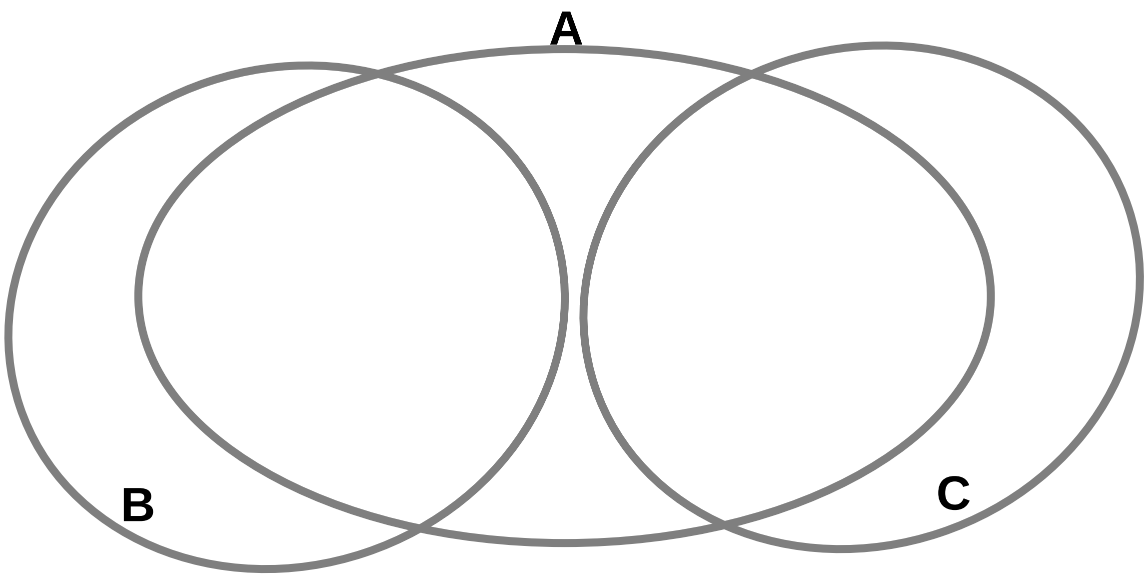


Simple Greedy Heuristic

- **Goal: Maximize the covered area**



When Greedy Heuristic Fails?



- **Goal:** Maximize the size of the covered area
- Greedy first picks A and then C
- But the optimal way would be to pick B and C

Approximation Guarantee

- **<u>Greedy</u> produces a solution *A* where: $F(A) \geq (1\text{-}1/e)*OPT$** $(F(A) \geq 0.63*OPT)$

  [Nemhauser, Fisher, Wolsey '78]

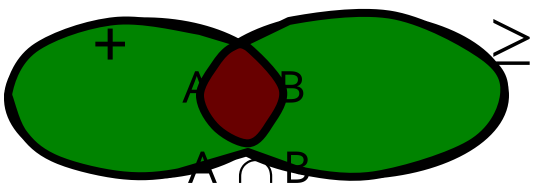
- **Claim holds for functions F(·) with 2 properties:**
  - ***F* is monotone:** (adding more docs doesn't decrease coverage)
    if $A \subseteq B$ then $F(A) \leq F(B)$ and $F(\{\})=0$
  - ***F* is submodular:**
    adding an element to a set gives less improvement than adding it to one of its subsets

Submodularity: Definition

Definition:

- Set function ***F(·)*** is called **submodular** if:
  For all $\boldsymbol{A,B \subseteq W}$:

$$F(A) + F(B) \geq F(A \cup B) + F(A \cap B)$$



+

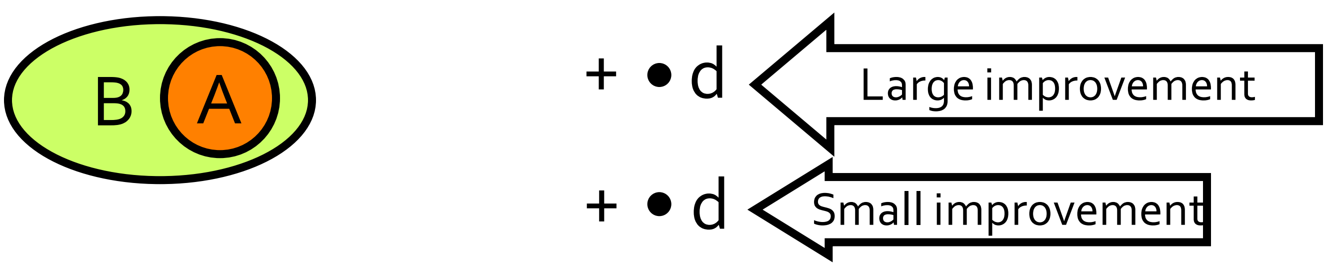
Submodularity: Or equivalently

- **Diminishing returns characterization**

Equivalent definition:

- Set function $F(\cdot)$ is called **submodular** if:
  For all $A \subseteq B$, $s \notin B$:

$$\underbrace{F(A \cup d) - F(A)}_{\text{Gain of adding } d \text{ to a small set}} \geq \underbrace{F(B \cup d) - F(B)}_{\text{Gain of adding } d \text{ to a large set}}$$

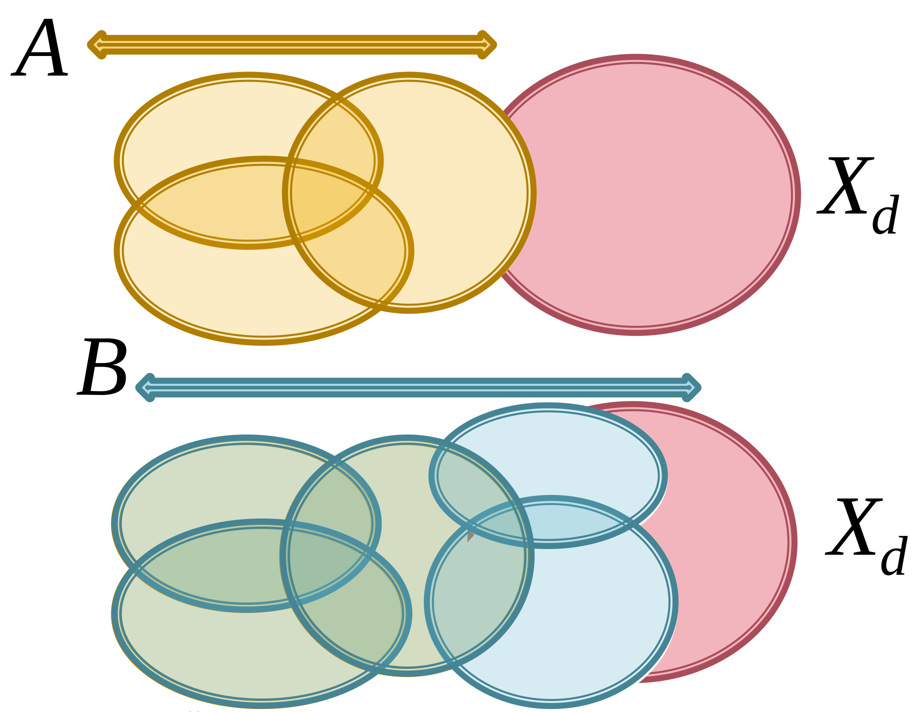


Example: Set Cover

- $F(\cdot)$ is **submodular**: $A \subseteq B$

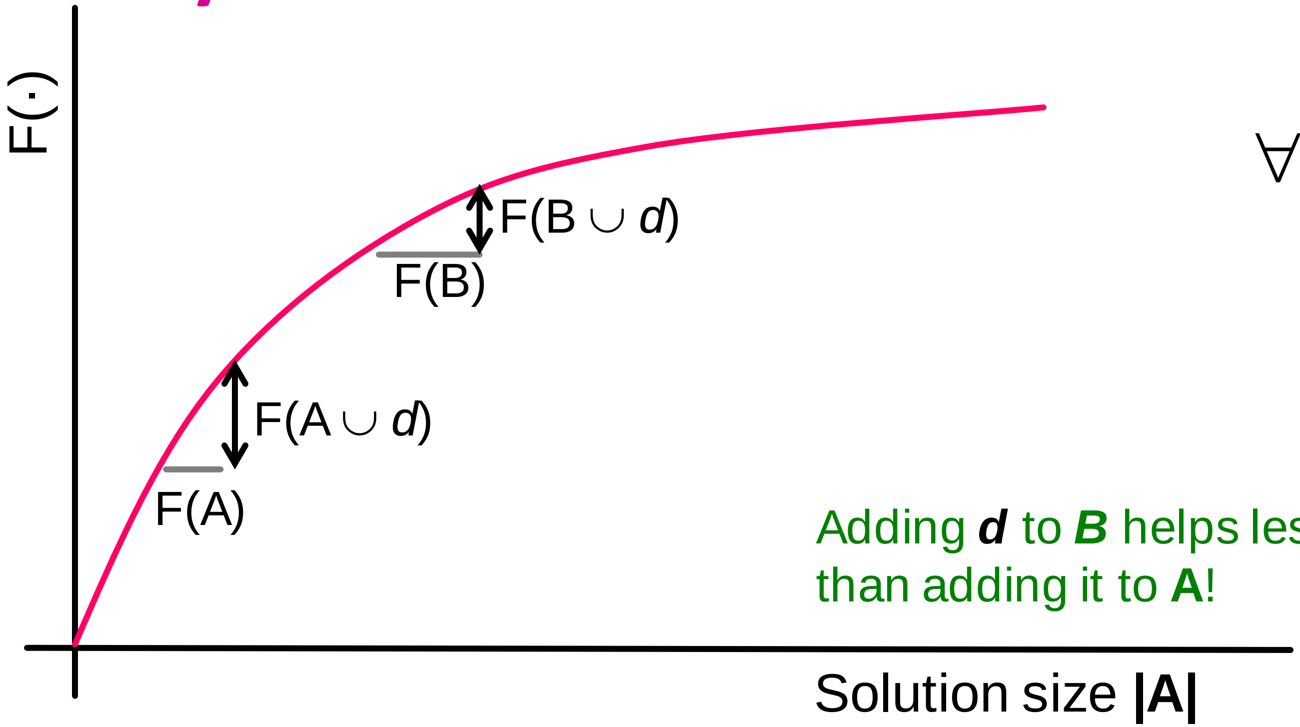
$$\underbrace{F(A \cup d) - F(A)}_{\text{Gain of adding } X_d \text{ to a small set}} \geq \underbrace{F(B \cup d) - F(B)}_{\text{Gain of adding } X_d \text{ to a large set}}$$

- **Natural example:**
  - Sets $X_1, \dots, X_m$
  - $F(A) = |\bigcup_{d \in A} X_d|$ **(size of the covered area)**
  - **Claim:** $\boldsymbol{F(A)}$ **is submodular!**



Submodularity– Diminishing returns

- **Submodularity is discrete analogue of concavity**



$\forall A \subseteq B$

Adding ***d*** to ***B*** helps less than adding it to **A**!

$$\underbrace{F(A \cup d) - F(A)}_{\text{Gain of adding } X_d \text{ to a small set}} \geq \underbrace{F(B \cup d) - F(B)}_{\text{Gain of adding } X_d \text{ to a large set}}$$

Submodularity & Concavity

- **Marginal gain:**

$$\Delta_F(d|A) = F(A \cup X_d) - F(A)$$

- **Submodular:**

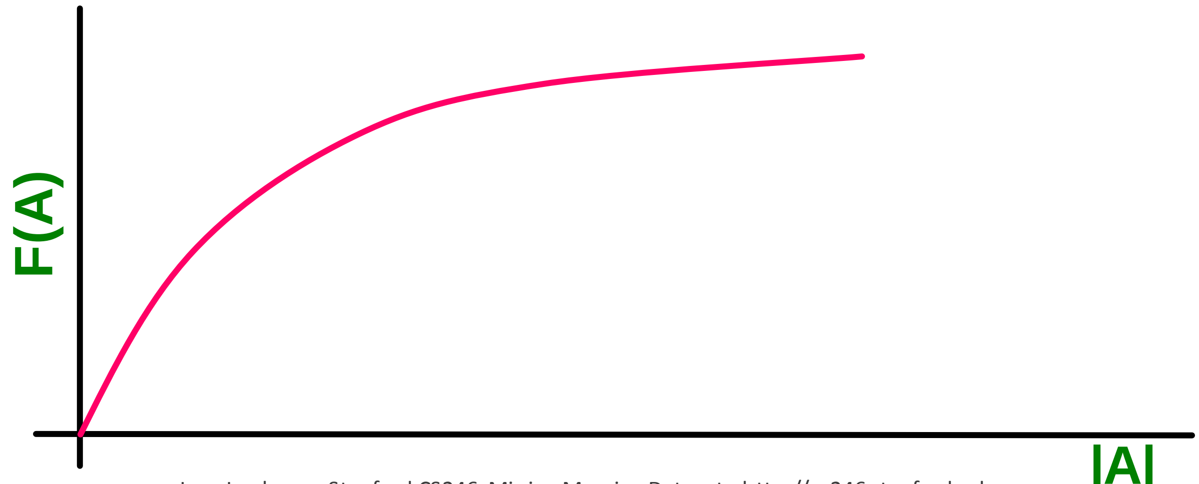
$$A \subseteq B$$

$$F(A \cup d) - F(A) \geq F(B \cup d) - F(B)$$

- **Concavity:**

$$a \leq b$$

$$f(a+d) - f(a) \geq f(b+d) - f(b)$$

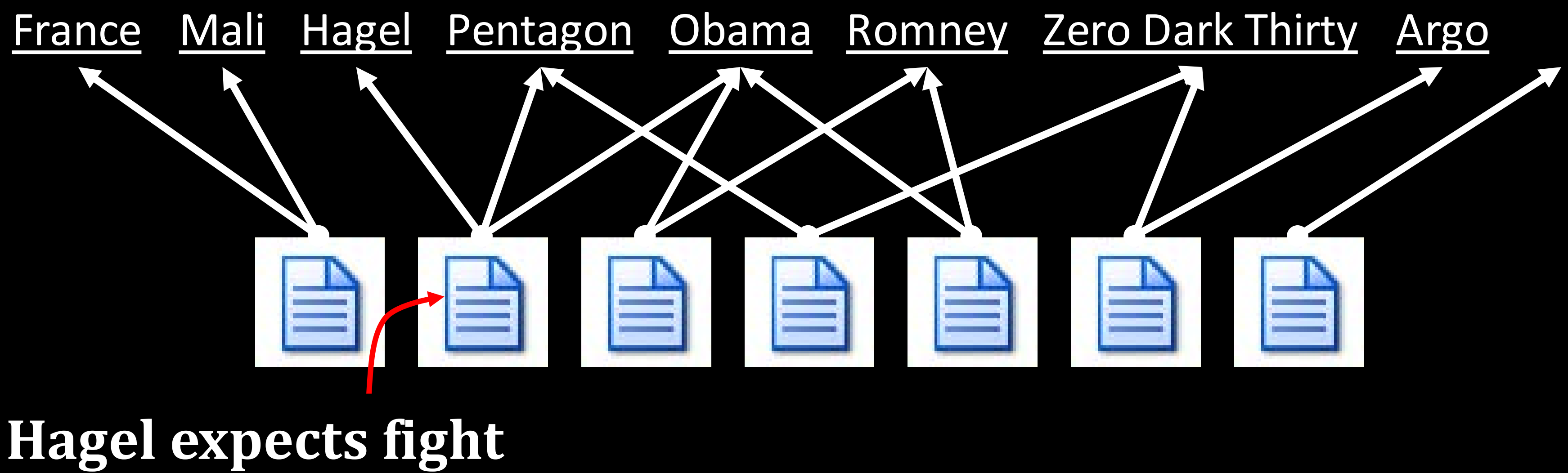


Submodularity: Useful Fact

- Let $F_1 \dots F_m$ be **submodular** and $\lambda_1 \dots \lambda_m > 0$ then $F(A) = \sum_i^m \lambda_i F_i(A)$ **is submodular**
  - **Submodularity is closed under non-negative linear combinations!**
- **This is an extremely useful fact:**
  - **Average of submodular functions is submodular:** $F(A) = \sum_i P(i) \cdot F_i(A)$
  - **Multicriterion optimization:** $F(A) = \sum_i \lambda_i F_i(A)$

Back to our problem

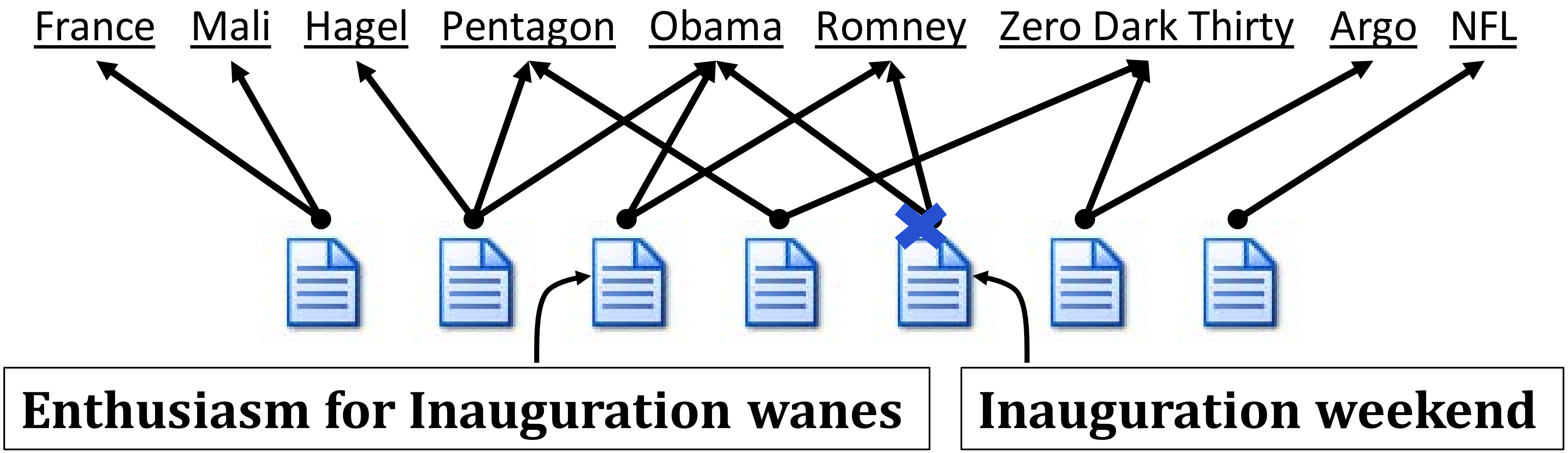
- **Q: What is being covered?**
- **A: Concepts** (In our case: Named entities)



- **Q: Who is doing the covering?**
- **A: Documents**

Back to our Concept Cover Problem

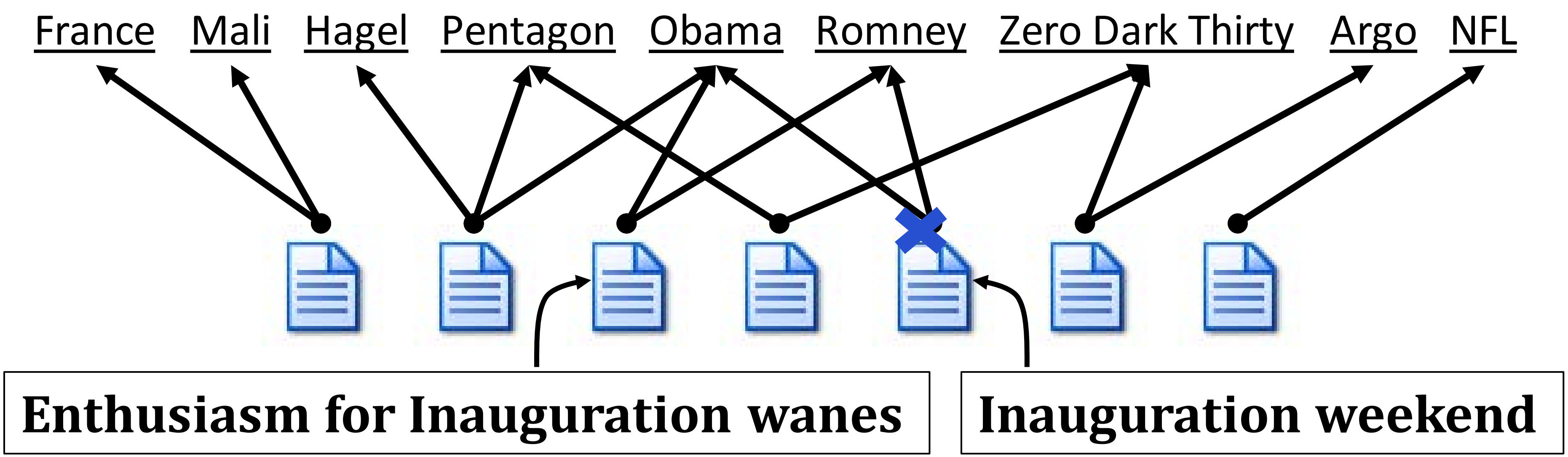
- **Objective:** **pick *k* docs that cover most concepts**



- ***F(A):* the number of concepts covered by *A***
  - ***Elements…concepts, Sets … concepts in docs***
  - ***F(A)*** is submodular and monotone!
  - We can use **greedy** to optimize ***F***

The Set Cover Problem

- **Objective:** pick ***k*** docs that cover most concepts



The good:

Penalizes redundancy

Submodular

The bad:

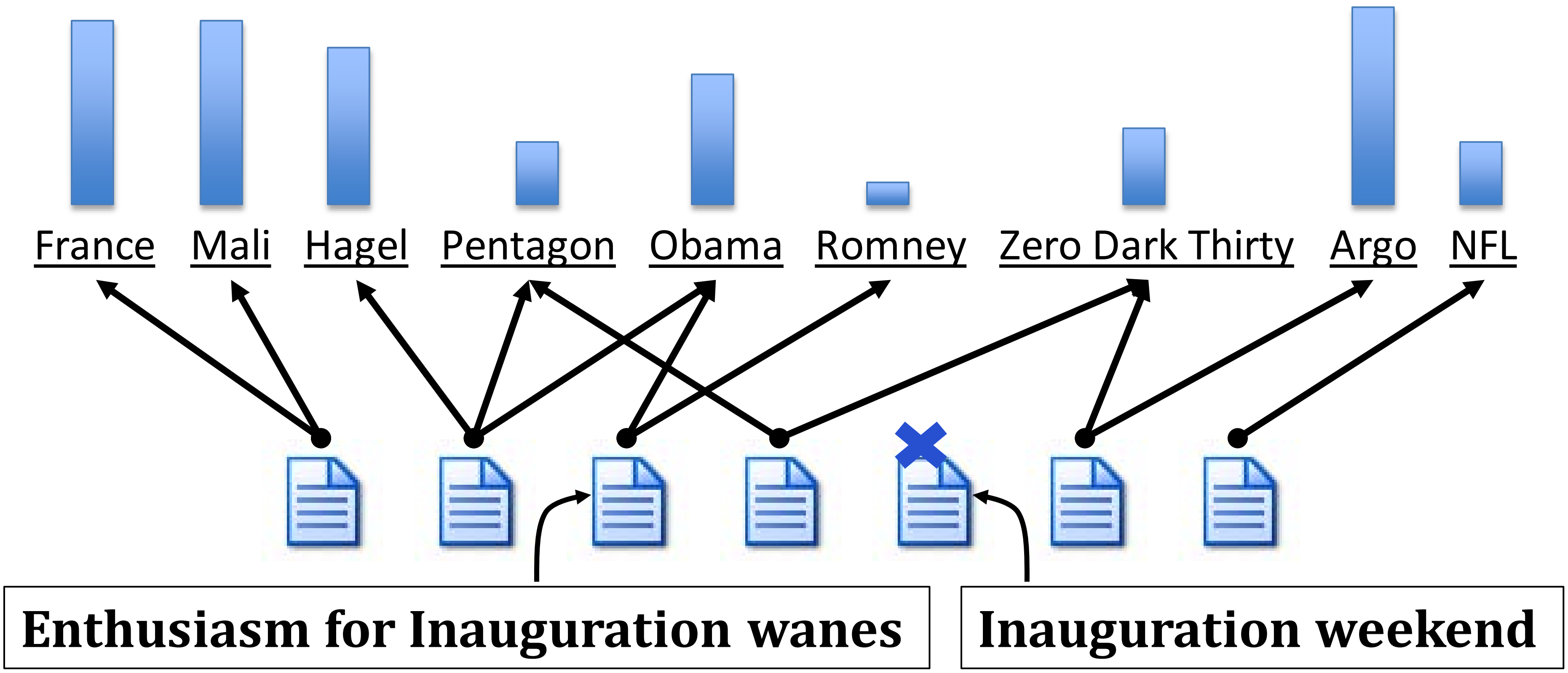
Concept importance?

All-or-nothing too harsh

Probabilistic Set Cover

Concept importance?

- **Objective:** pick ***k*** docs that cover most concepts



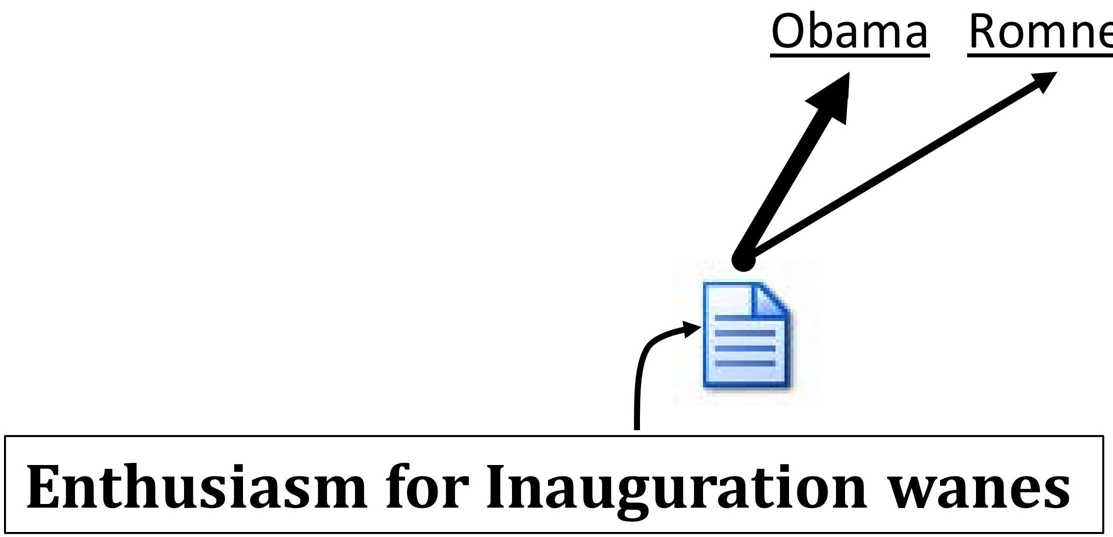
- **Each concept c has importance weight w_c**

All-or-nothing too harsh

- **Document coverage function**

$\mathrm{cover}_d(c) =$ **probability** document **d** covers concept **c**

[e.g., how strongly **d** covers **c**]



Probabilistic Set Cover

- **Document coverage function:**

  $\text{cover}_d(c) =$ **probability** document **d** covers concept **c**

  - **Cover$_d$(c)** can model how relevant is concept **c** for user **u**

- **Set coverage function:**

  $$\text{cover}_{\mathcal{A}}(c) = 1 - \prod_{d \in \mathcal{A}} (1 - \text{cover}_d(c))$$

  - Prob. that at least one document in **A** covers **c**

- **Objective:**

  concept weights

  $$\max_{\mathcal{A}:|\mathcal{A}|\leq k} F(\mathcal{A}) = \sum_c w_c \ \text{cover}_{\mathcal{A}}(c)$$

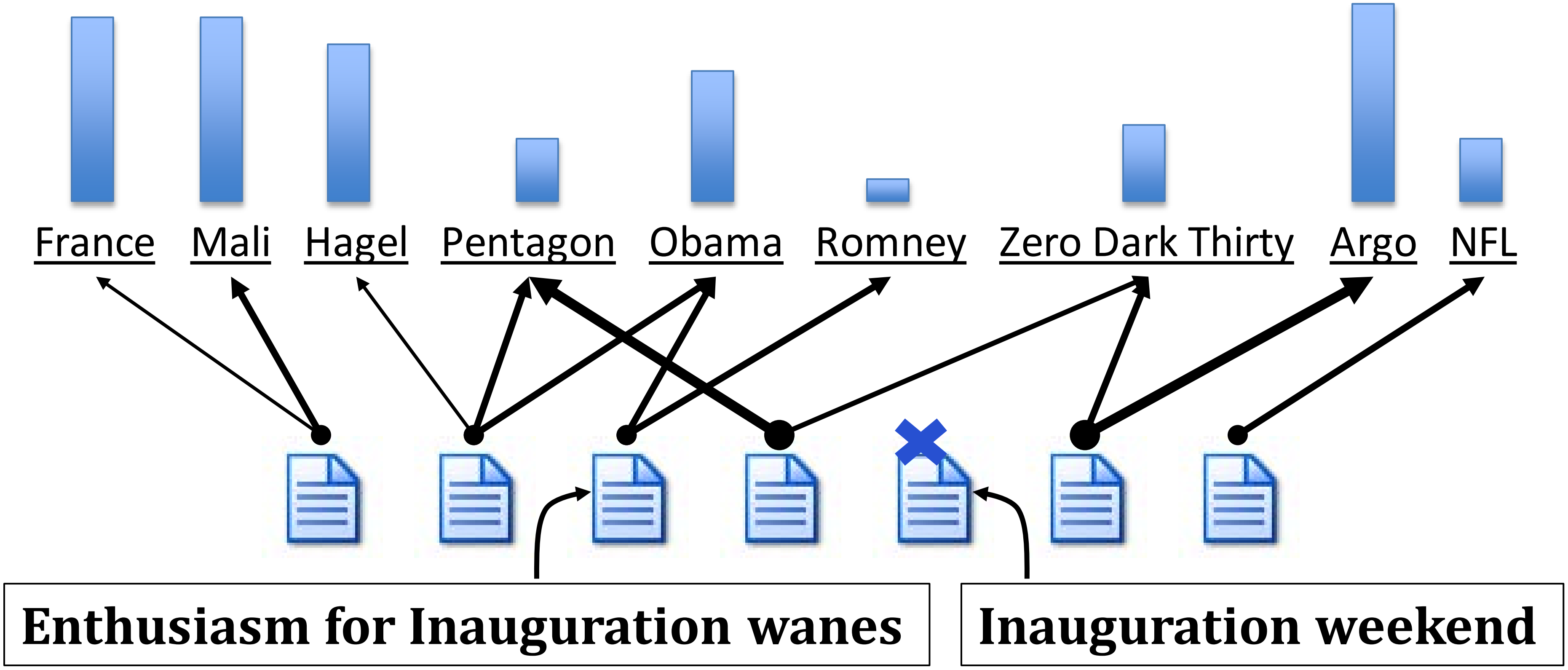
Optimizing F(A)

$$\max_{\mathcal{A}:|\mathcal{A}|\leq k} F(\mathcal{A}) = \sum_{c} w_c \; \text{cover}_{\mathcal{A}}(c)$$

- The objective function is also **submodular**
  - Intuitive **diminishing returns** property
  - Greedy algorithm leads to a (1 – 1/e) ~ 63% approximation, i.e., a **near-optimal** solution

Summary: Probabilistic Set Cover

- **Objective:** pick ***k*** docs that cover most concepts



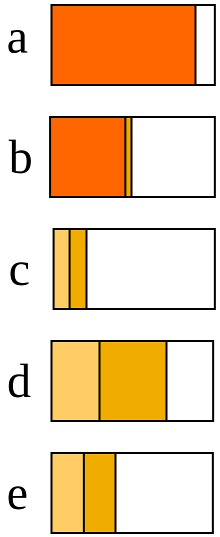
- Each concept c has importance weight w_c
- Documents partially cover concepts: $\mathbf{cover}_d(c)$

Lazy Optimization of Submodular Functions

Submodular Functions

Greedy

Marginal gain:
F(A∪x)-F(A)



Add document with highest marginal gain

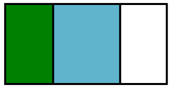
- **Greedy** algorithm is **slow!**
  - At each iteration we need to re-evaluate marginal gains of **all remaning documents**
  - **Runtime $O(|D| \cdot K)$ for selecting K documents out of the set of D of them**

[Leskovec et al., KDD '07]

Speeding up Greedy

- **In round i:** So far we have $A_{i-1} = \{d_1, \dots, d_{i-1}\}$
  - Now we pick $\mathbf{d}_i = \arg\max_{d \in V} F(A_{i-1} \cup \{d\}) - F(A_{i-1})$
    - Greedy algorithm **maximizes the "marginal benefit"**
      $\Delta_i(d) = F(A_{i-1} \cup \{d\}) - F(A_{i-1})$
- **By submodularity property:**
  $F(A_i \cup \{d\}) - F(A_i) \geq F(A_j \cup \{d\}) - F(A_j)$ for $i < j$
- **Observation: By submodularity:**
  For every $d \in D$
  $\Delta_i(d) \geq \Delta_j(d)$ for $i < j$ since $A_i \subseteq A_j$
- **Marginal benefits $\Delta_i(d)$ only shrink!**
  (as i grows)

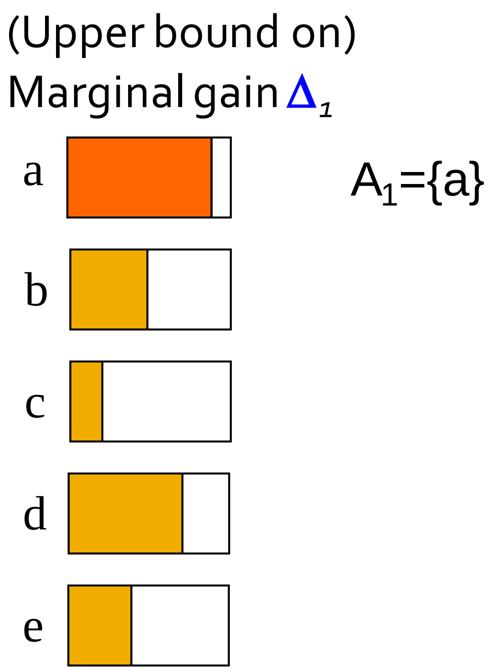
$\Delta_i(d) \geq \Delta_j(d)$

d


Selecting document ***d*** in step ***i*** covers more words than selecting ***d*** at step ***j*** (j>i)

Lazy Greedy

- **Idea:**
  - Use Δ_i as upper-bound on Δ_j ($j > i$)
- **Lazy Greedy:**
  - Keep an ordered list of marginal benefits Δ_i from previous iteration
  - Re-evaluate Δ_i only for top node
  - Re-sort and prune



$$F(A \cup \{d\}) - F(A) \geq F(B \cup \{d\}) - F(B) \quad A \subseteq B$$

[Leskovec et al., KDD '07]

Lazy Greedy

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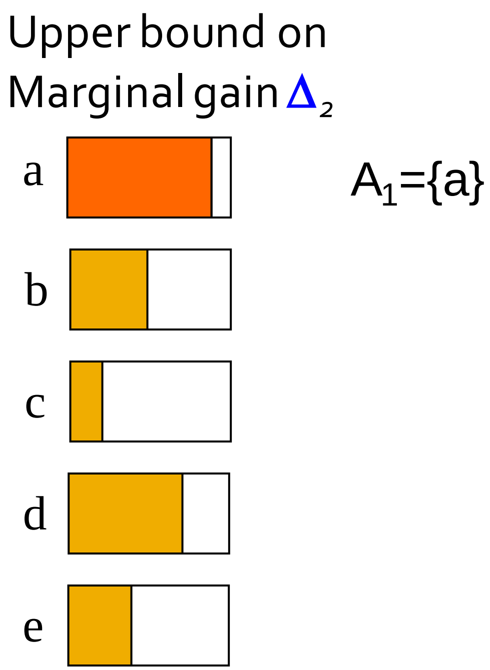

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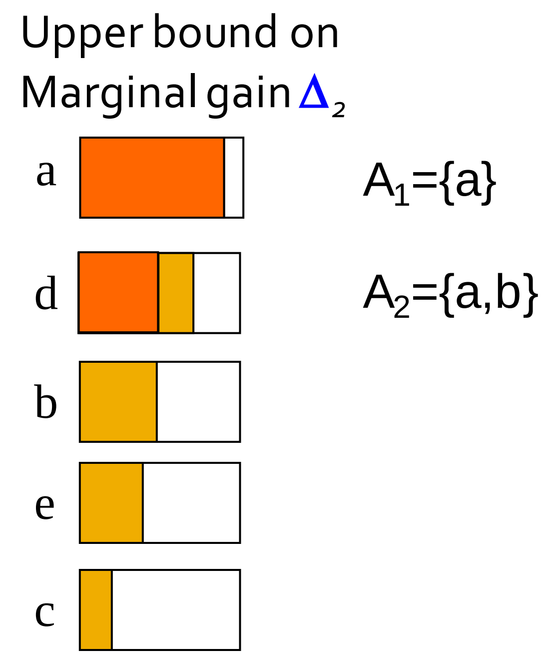
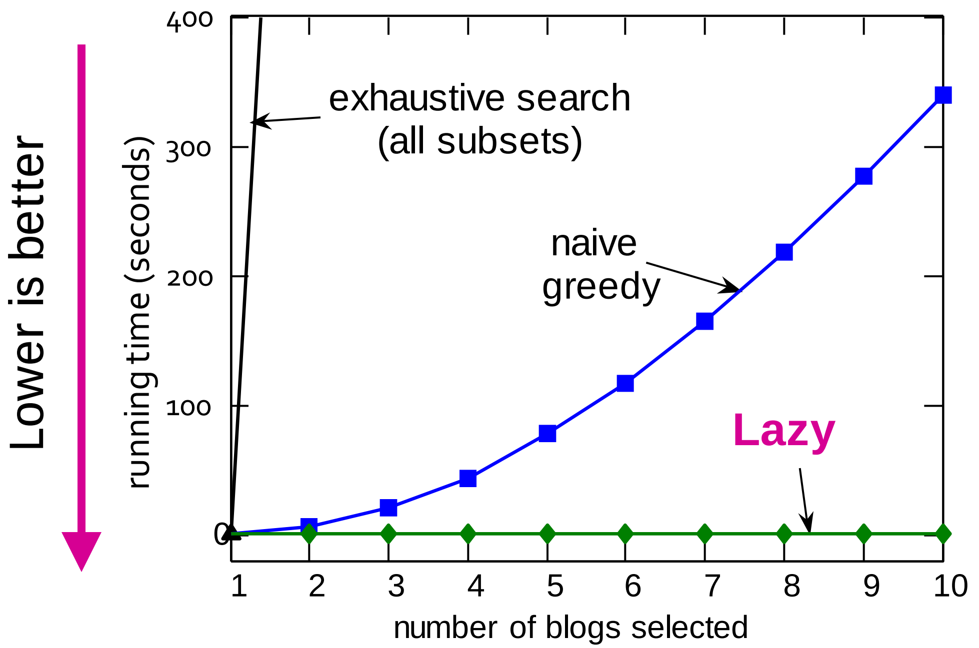


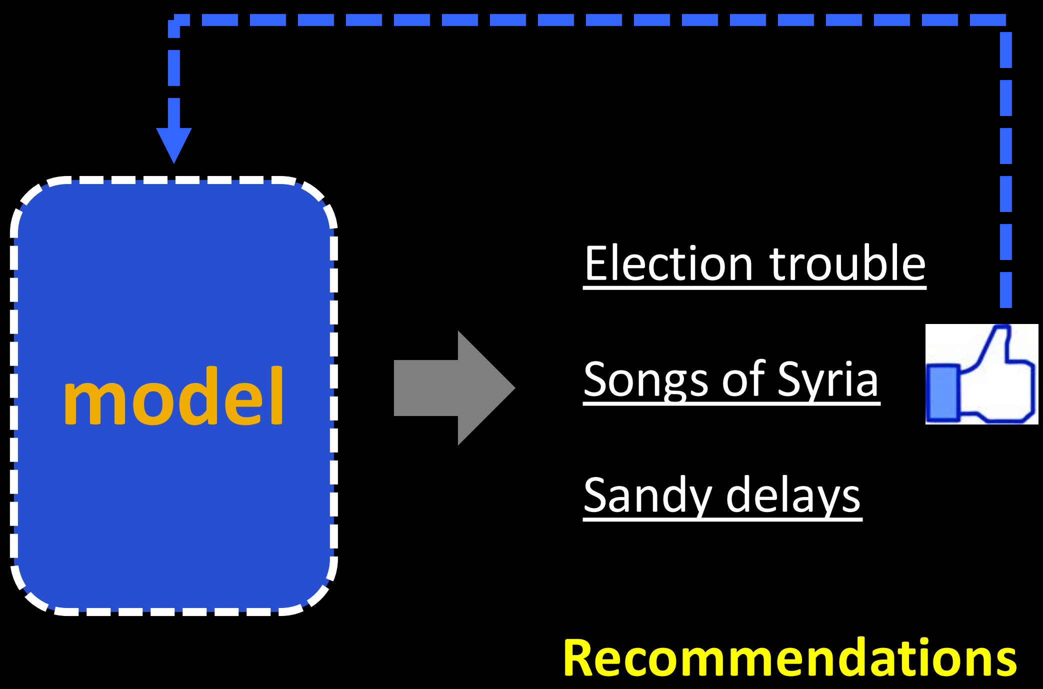
$$F(A \cup \{d\}) - F(A) \geq F(B \cup \{d\}) - F(B) \qquad A \subseteq B$$

Summary so far

- **Summary so far:**
  - Diversity can be formulated as a set cover
  - Set cover is submodular optimization problem
  - Can be (approximately) solved using greedy algorithm
  - Lazy-greedy gives significant speedup

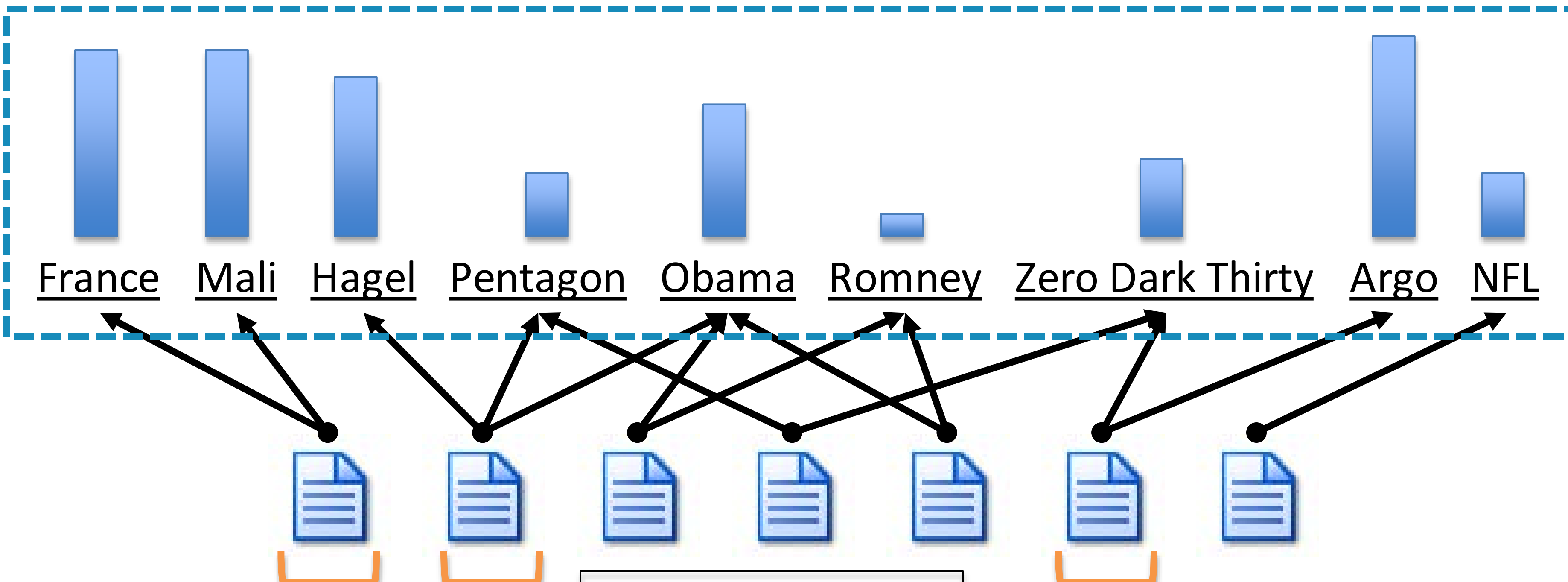


But what about **personalization**?



Concept Coverage

We assumed same concept weighting for all users



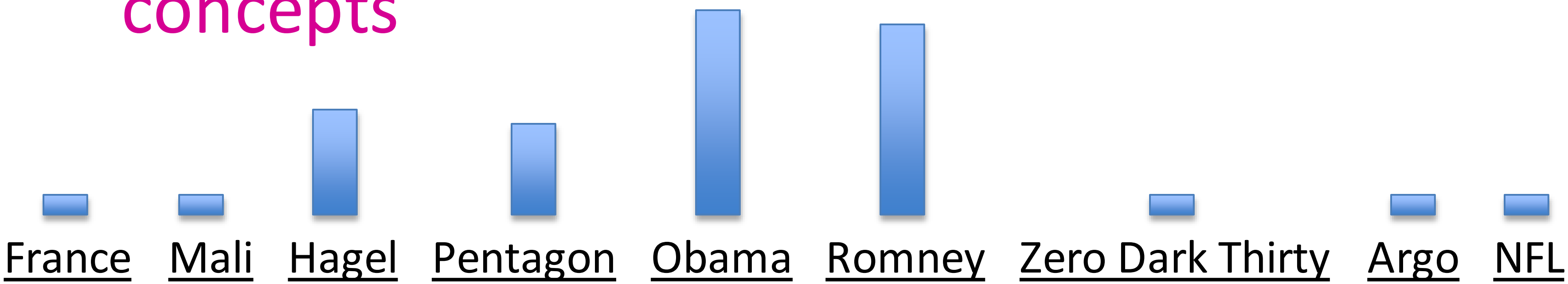
France intervenes

Chuck for Defense

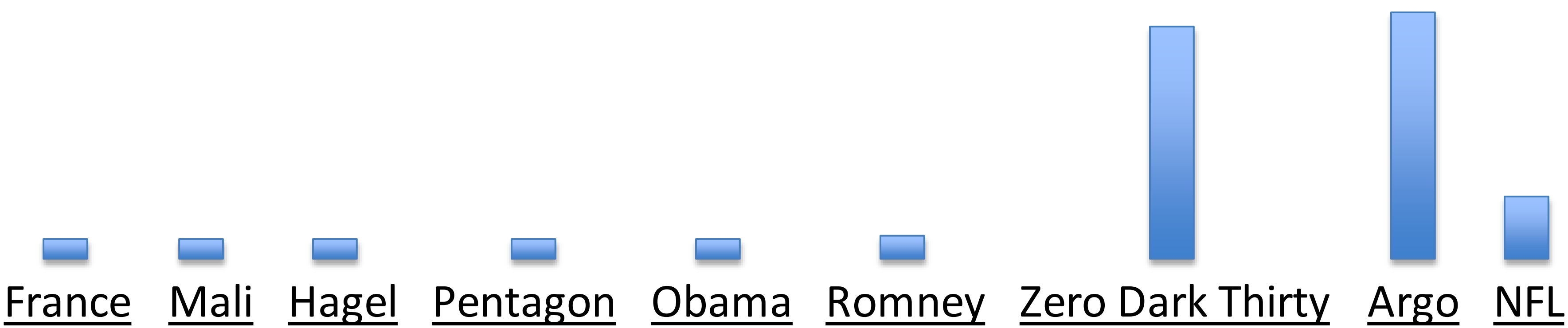
Argo wins big

Personal Concept Weights

- Each user has **different** preferences over concepts



politico



movie buff

Personal concept weights

- Assume each user ***u*** has **different** preference vector $\boldsymbol{w_c^{(u)}}$ over concepts ***c***

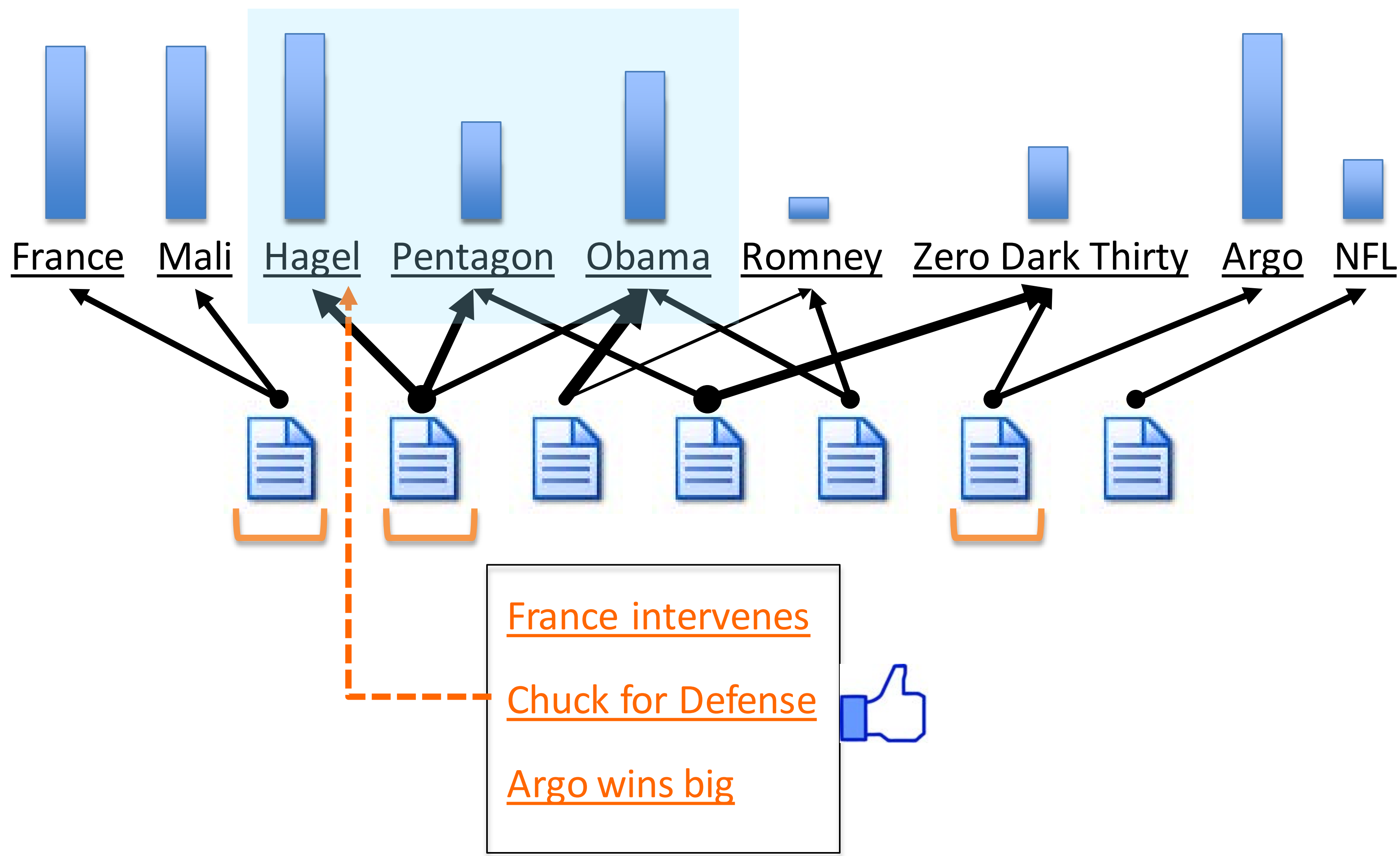
$$\max_{\mathcal{A}:|\mathcal{A}|\leq k} F(\mathcal{A}) = \sum_c w_c \ \text{cover}_{\mathcal{A}}(c)$$

$$\Downarrow$$

$$\max_{\mathcal{A}:|\mathcal{A}|\leq k} F(\mathcal{A}) = \sum_c w_c^{(u)} \ \text{cover}_{\mathcal{A}}(c)$$

- **Goal:** Learn personal concept weights from user feedback

Interactive Concept Coverage



Multiplicative Weights (MW)

- **Multiplicative Weights** algorithm
  - Assume each concept $\boldsymbol{c}$ has weight $\boldsymbol{w_c}$
  - We recommend document $\boldsymbol{d}$ and receive feedback, say $\boldsymbol{r} =$ **+1** or **-1**
  - **Update the weights:**
    - **If $\boldsymbol{c} \in \boldsymbol{X_d}$ then $\boldsymbol{w_c} = \boldsymbol{\beta^r w_c}$**
    - **If $\boldsymbol{c} \notin \boldsymbol{X_d}$ then $\boldsymbol{w_c} = \boldsymbol{\beta^{-r} w_c}$**
      - If concept **c** appears in $\mathbf{X_d}$ and we received positive feedback **r=+1** then we increase the weight $\mathbf{w_c}$ by multiplying it by $\boldsymbol{\beta}$ ($\boldsymbol{\beta > 1}$) otherwise we decrease the weight (divide by $\boldsymbol{\beta}$)
    - **Normalize weights so that $\sum_c \boldsymbol{w_c} = \mathbf{1}$**

Summary of the Algorithm

- **Steps of the algorithm:**
  1. Identify **items** to recommend from
  2. Identify **concepts** [what makes items redundant?]
  3. **Weigh** concepts by general importance
  4. Define **item-concept coverage function**
  5. **Select** items using probabilistic set cover
  6. Obtain **feedback**, **update** weights

Summary: Submodularity

	Maximization	Minimization
Unconstrained	NP-hard, but well-approximable (if nonnegative)	Polynomial time! Generally inefficent (n^6), but can exploit special cases (cuts; symmetry; decomposable; ...)
Constrained	NP-hard but well-approximable „Greedy-(like)“ for cardinality, matroid constraints; Non-greedy for more complex (e.g., connectivity) constraints	NP-hard; hard to approximate, still useful algorithms