ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Submodularity in Machine Learning and Vision

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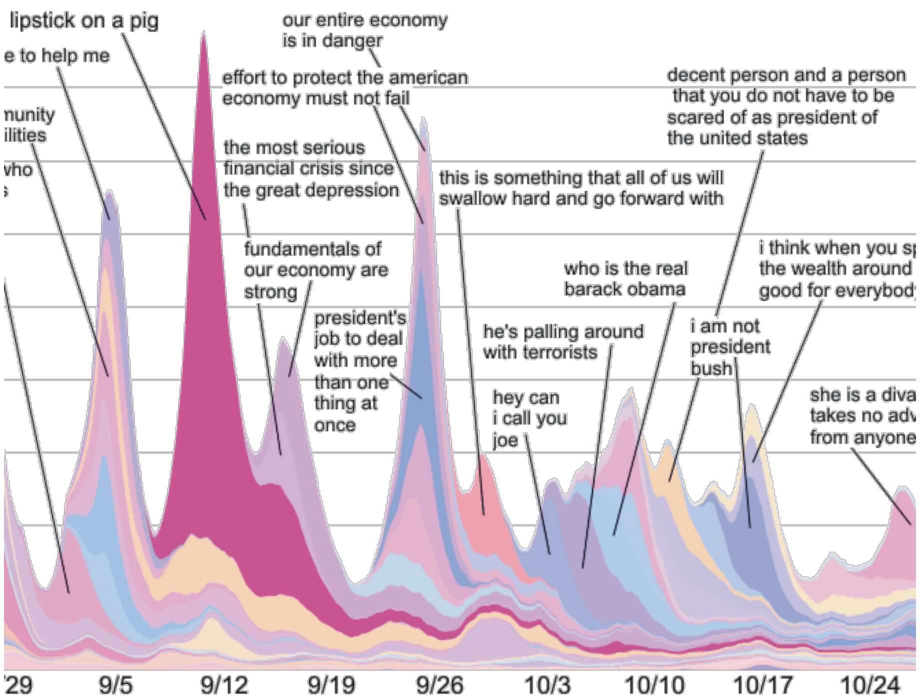
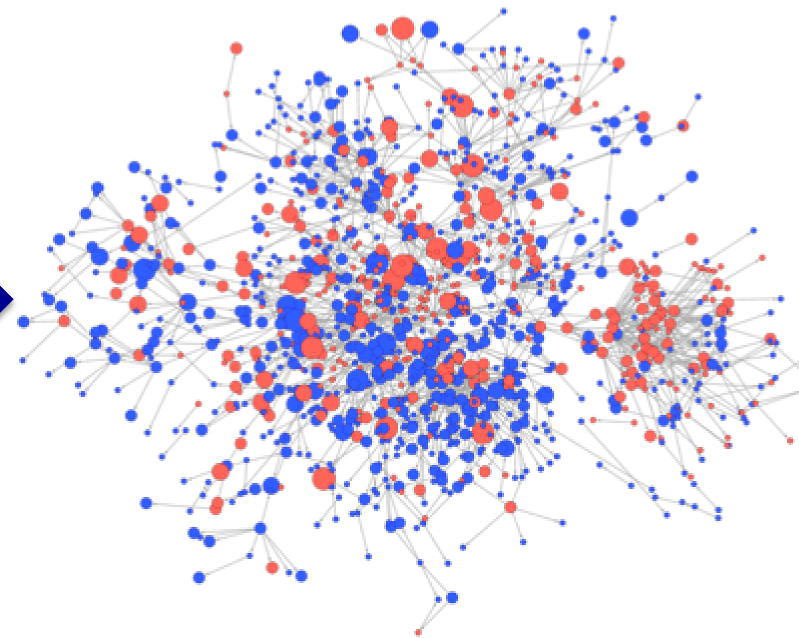
British Machine Vision Conference (BMVC) 2013
Bristol, UK

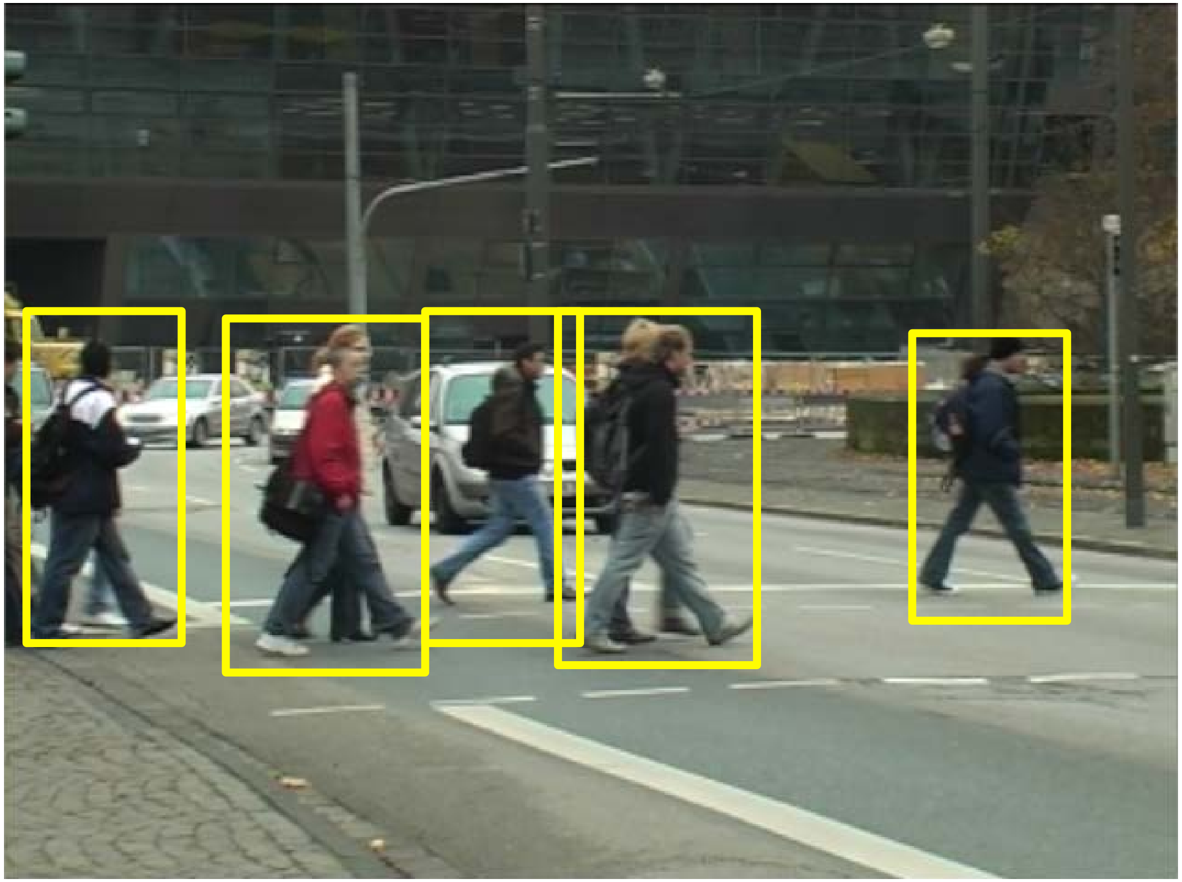
Network Inference





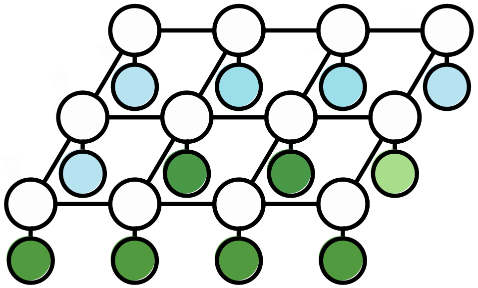
How to learn who influences whom?

Multiple object detection



How to locate multiple objects in an image?

Segmentation & MAP inference



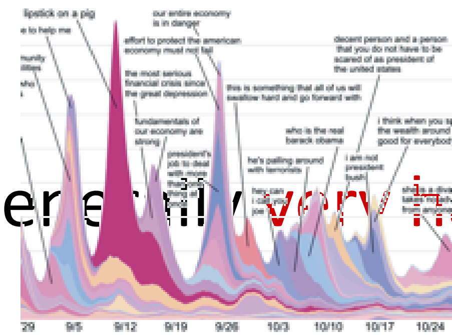
$$\max_x \; p(x \mid z)$$

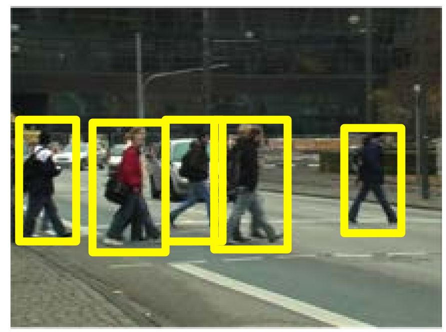
How find the MAP labeling in discrete graphical models *efficiently*?

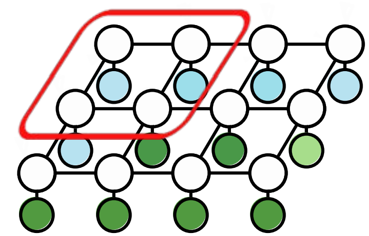
What's common?

- Formalization:

  Optimize a set function F(S) under constraints







- generally very hard

- but: structure helps!
  … if F is submodular, we can …
  - solve optimization problems with strong guarantees
  - solve complex structured learning problems

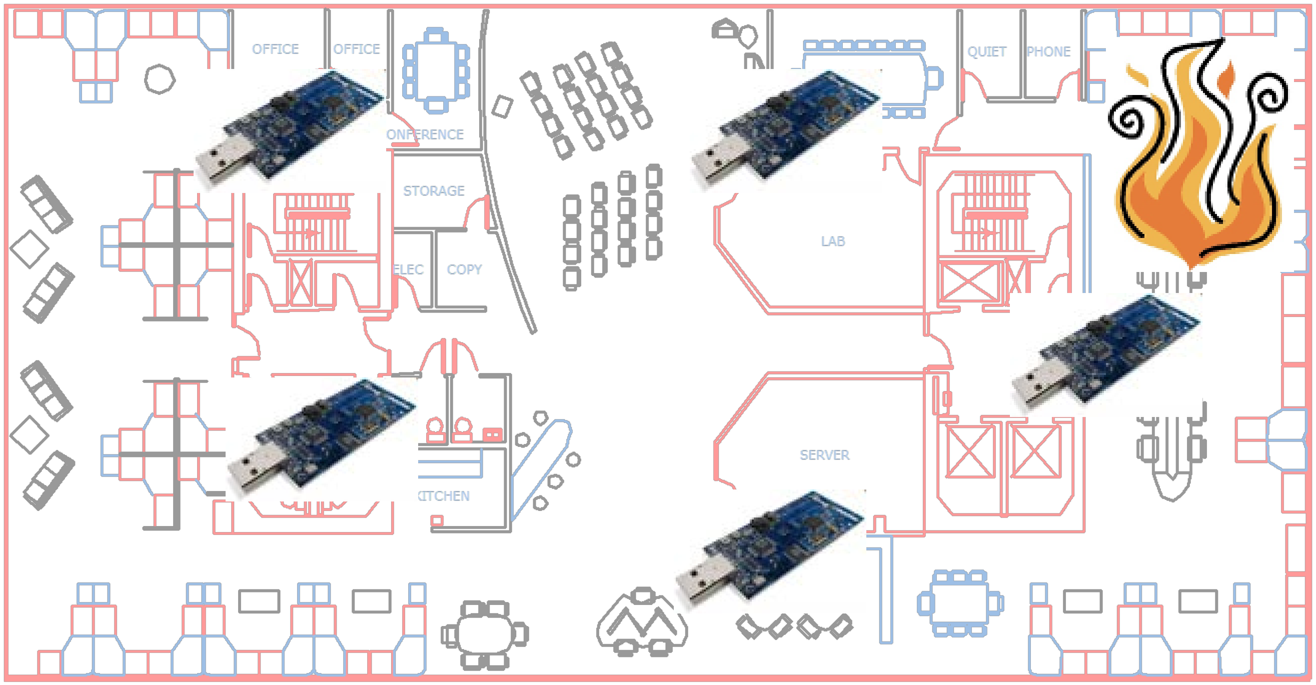
Outline

- What is submodularity?
- Optimization
  - Minimization
  - Maximization
- Applications
- Outlook and pointers

submodularity.org

slides, code, references, workshops, …

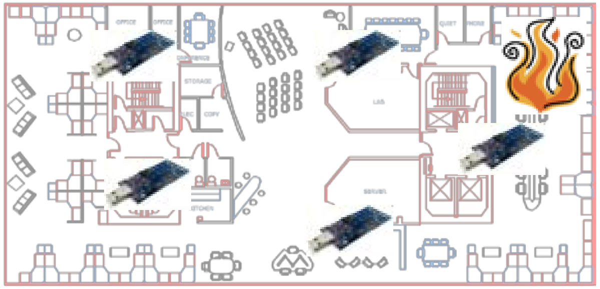
Example: placing sensors



Place sensors to monitor temperature

Set functions

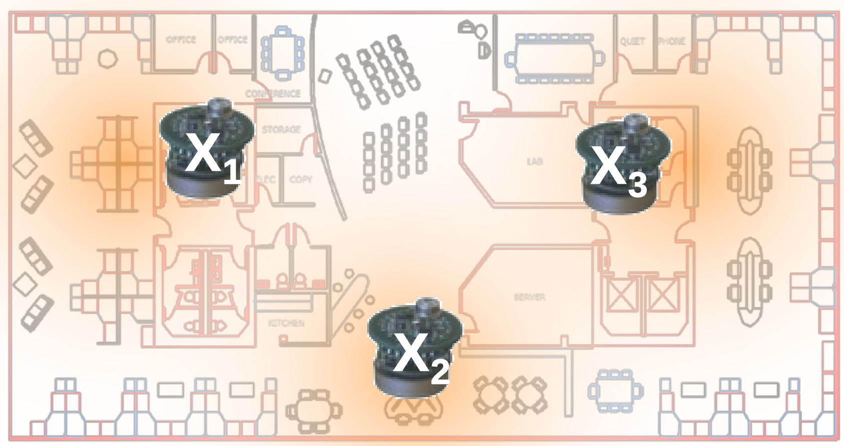
- finite ground set $V = \{1, 2, \ldots, n\}$
- set function $F : 2^V \to \mathbb{R}$



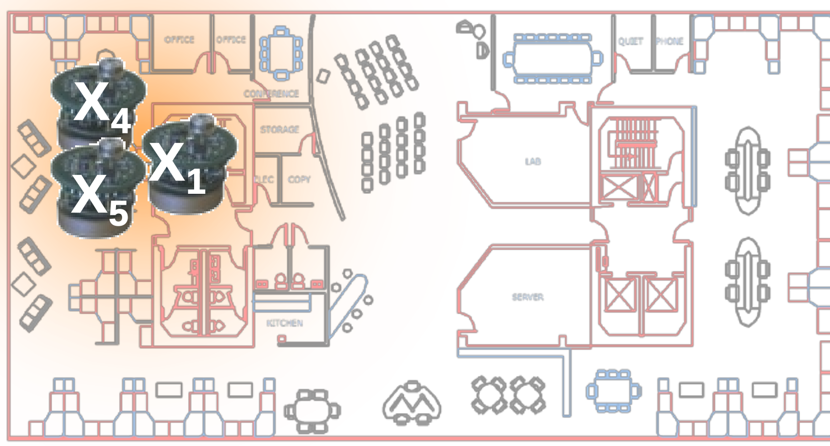
- will assume $F(\emptyset) = 0$ (w.l.o.g.)
- assume black box that can evaluate $F(A)$ for any $A \subseteq V$

Example: placing sensors

Utility $F(A)$ of having sensors at subset A of all locations



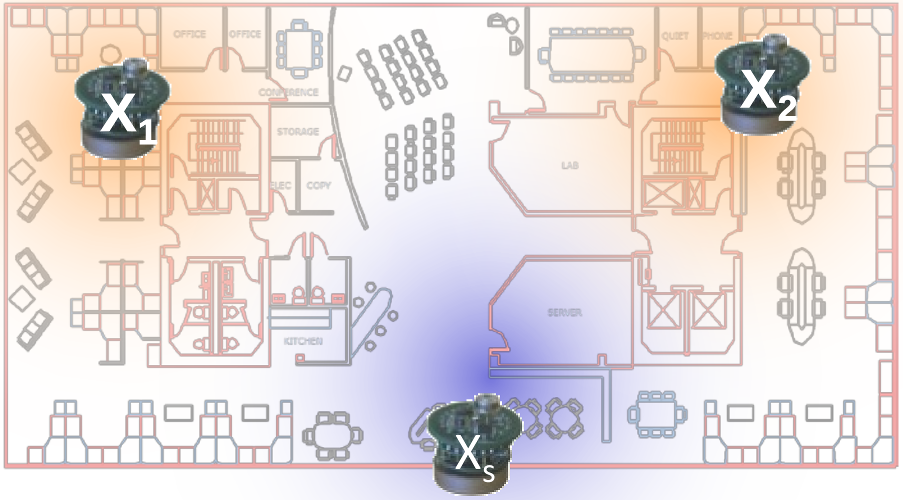
A={1,2,3}: Very informative
High value F(A)



A={1,4,5}: Redundant info
Low value F(A)

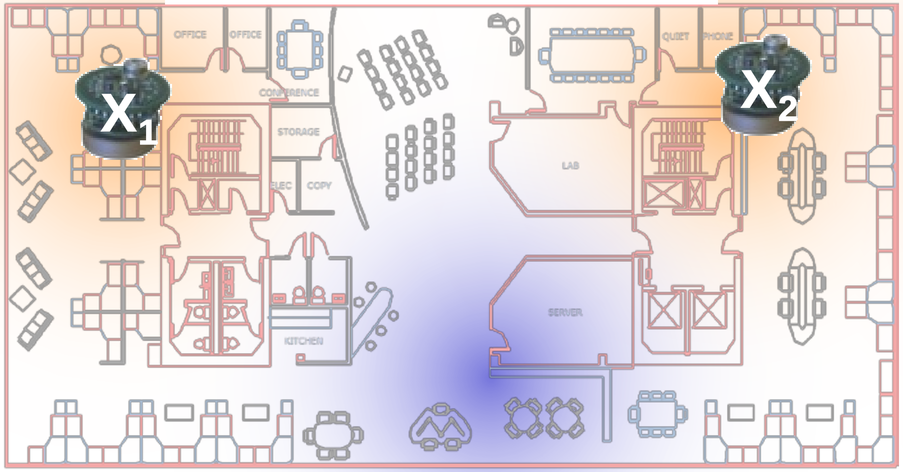
Marginal gain

- Given set function $F : 2^V \rightarrow \mathbb{R}$
- Marginal gain: $\Delta_F(s \mid A) = F(\{s\} \cup A) - F(A)$

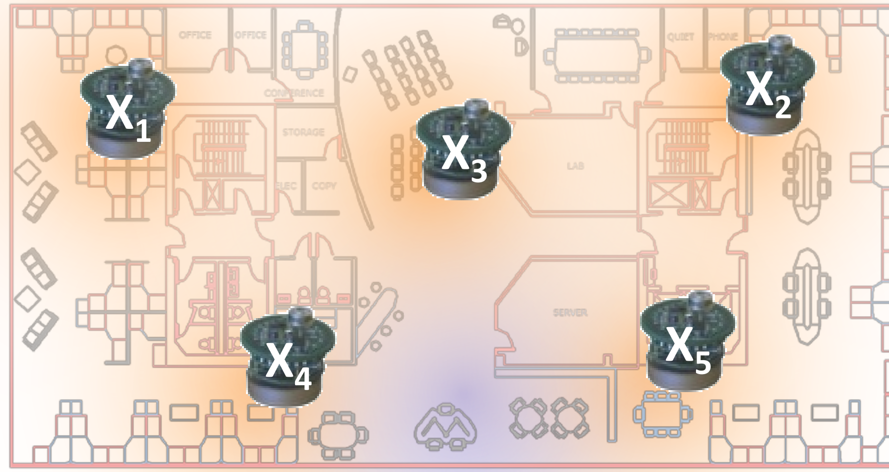


Decreasing gains: submodularity

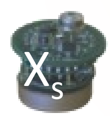
placement A = {1,2}



placement B = {1,…,5}



Big gain

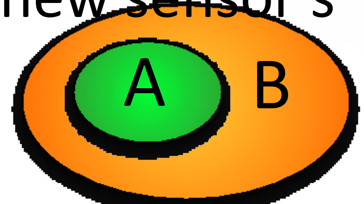


Adding *s* do … uch

small gain

new sensor s

+ • s



+ • s

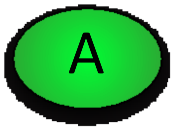
$$A \subseteq B \qquad F(A \cup s) - F(A) \quad \geq \quad F(B \cup s) - F(B)$$

$$s \notin B$$

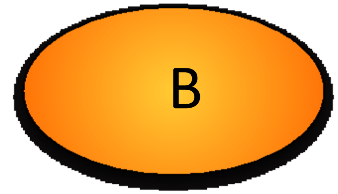
$$\Delta(s \mid A)$$

Equivalent characterizations

- Diminishing returns: for all $A \subseteq B$ and $s \notin B$



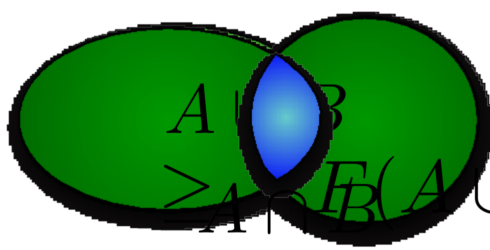
\+ • s



\+ • s

$$F(A \cup s) - F(A) \quad \geq \quad F(B \cup s) - F(B)$$

- Union-Intersection: for all $A, B \subseteq V$



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

Submodular, modular & supermodular

A set function F is called

- supermodular if -F is submodular
- modular if F is both submodular and supermodular. Such functions can be written as

$$F(A) = \sum_{i \in A} w_i$$

Questions

How do I prove my problem is submodular?

Why is submodularity useful?

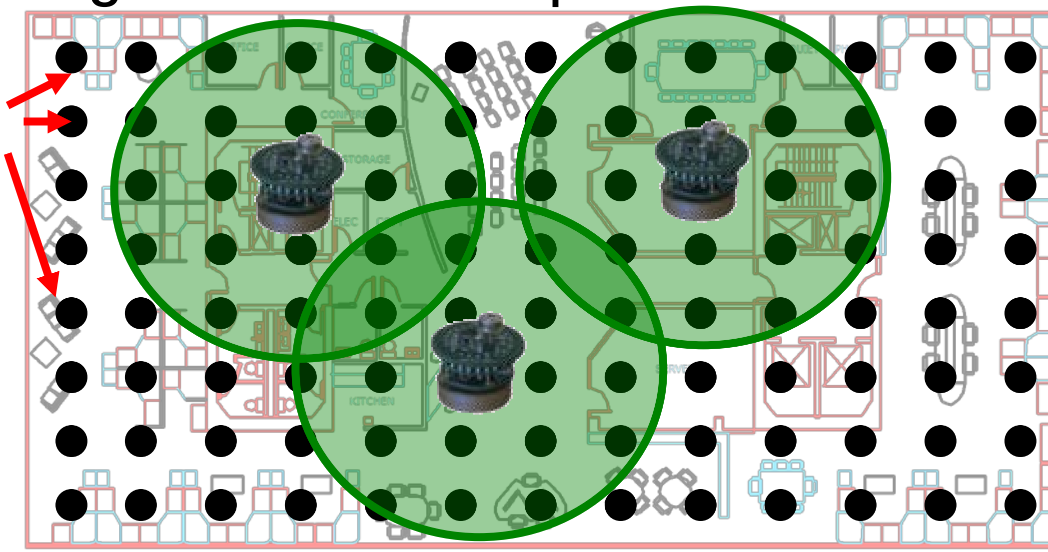
Example: Set cover

place sensors
in building

Node predicts
values of positions
with some radius

goal: cover floorplan with discs

Possible
locations
V



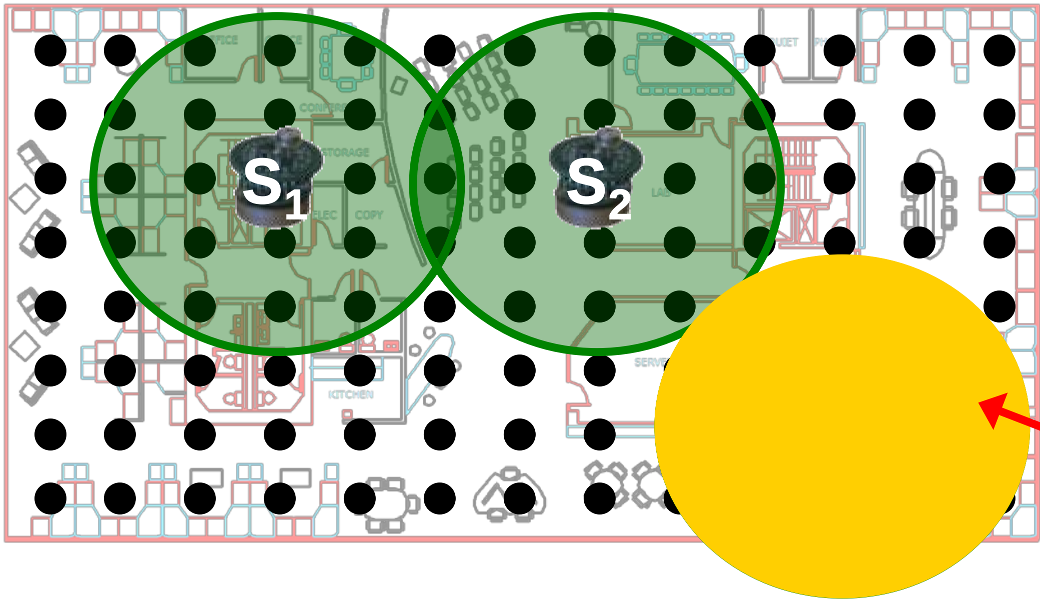
$A \subseteq V$: $F(A) =$
"area covered by sensors placed at A"

Formally:

Finite set W, collection of n subsets $S_i \subseteq W$

For $A \subseteq V$ define $F(A) = \left|\bigcup_{i \in A} S_i\right|$

Set cover is submodular

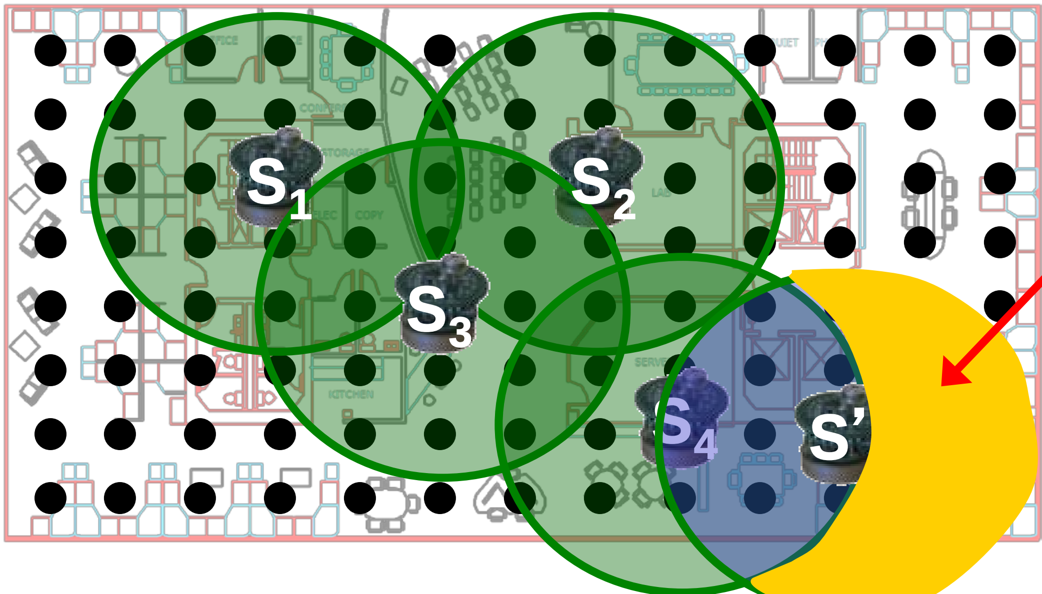


$A=\{s_1,s_2\}$

$F(A \cup \{s'\}) - F(A)$

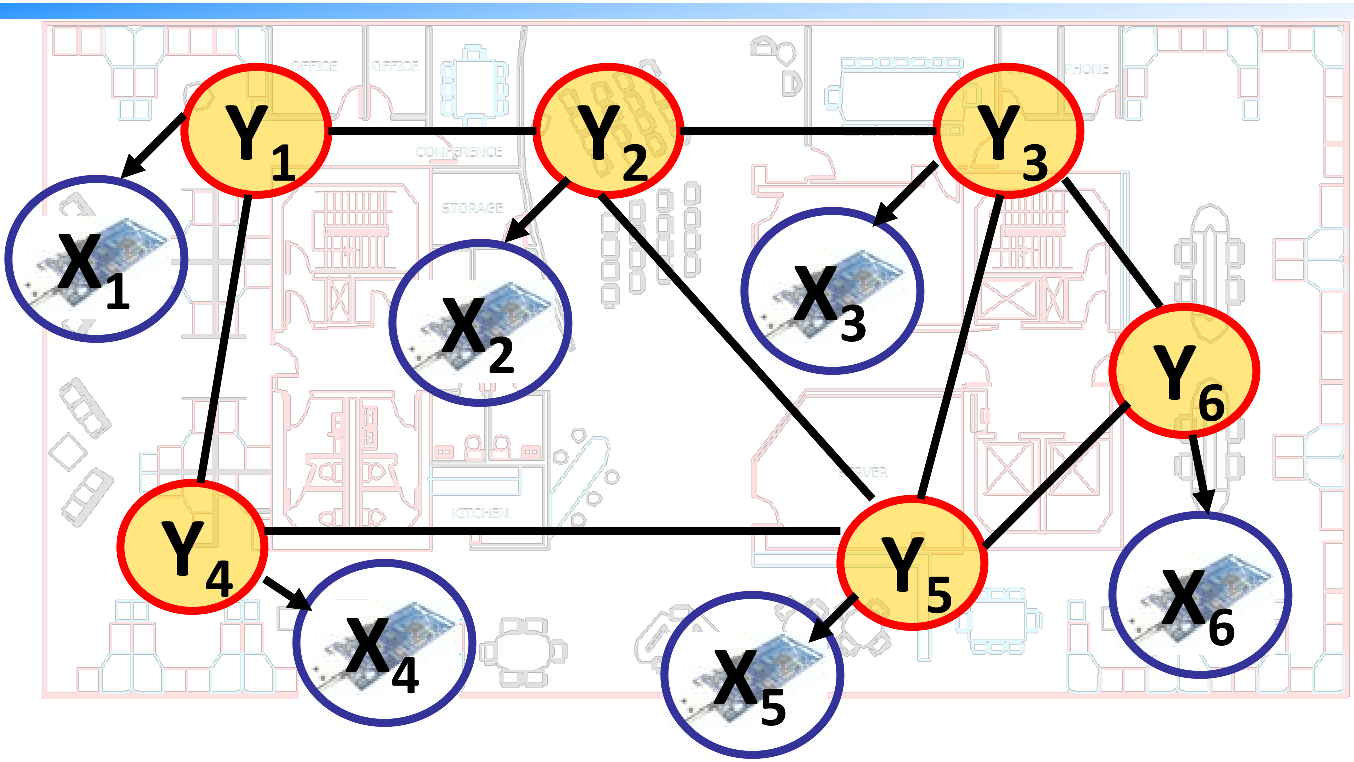
$\geq$

$F(B \cup \{s'\}) - F(B)$



$B = \{s_1,s_2,s_3,s_4\}$

More complex model for sensing



Y_s: temperature at location s

X_s: sensor value at location s

$X_s = Y_s + \text{noise}$

Joint probability distribution

$$P(X_1,\ldots,X_n,Y_1,\ldots,Y_n) = \underbrace{P(Y_1,\ldots,Y_n)}_{\textbf{Prior}}\ \underbrace{P(X_1,\ldots,X_n \mid Y_1,\ldots,Y_n)}_{\textbf{Likelihood}}$$

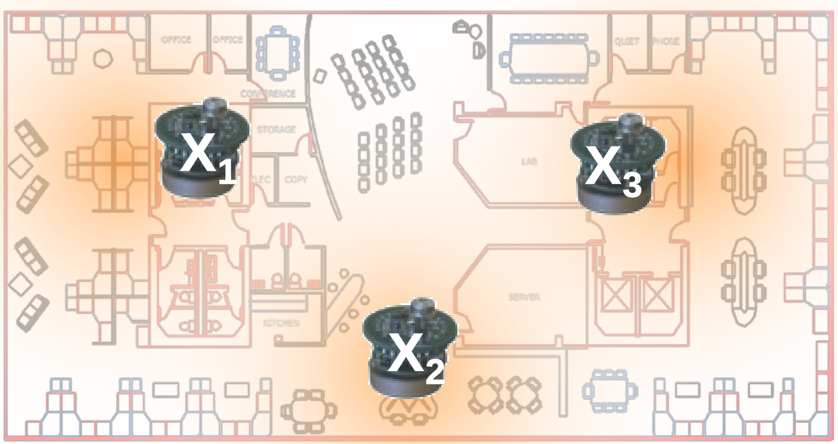
Example: Sensor placement

Utility of having sensors at subset A of all locations

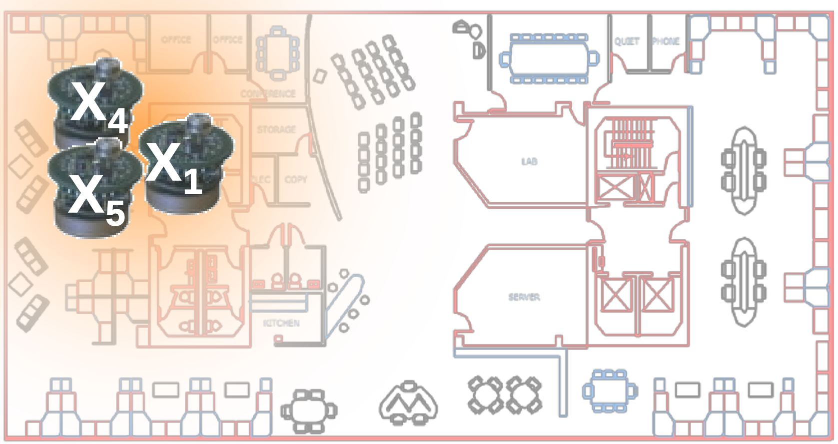
$$F(A) = H(\mathbf{Y}) - H(\mathbf{Y} \mid \mathbf{X}_A)$$

Uncertainty
about temperature Y
before sensing

Uncertainty
about temperature Y
after sensing



A={1,2,3}: High value F(A)



A={1,4,5}: Low value F(A)

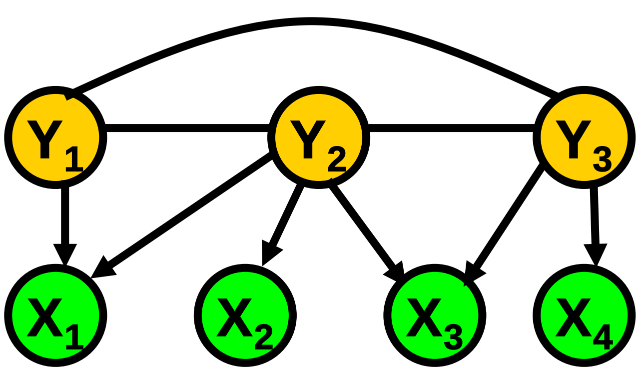
Submodularity of Information Gain

$Y_1,\ldots,Y_m$, X_1, …, X_n random variables

$F(A) = I(Y; X_A) = H(Y)-H(Y \mid X_A)$

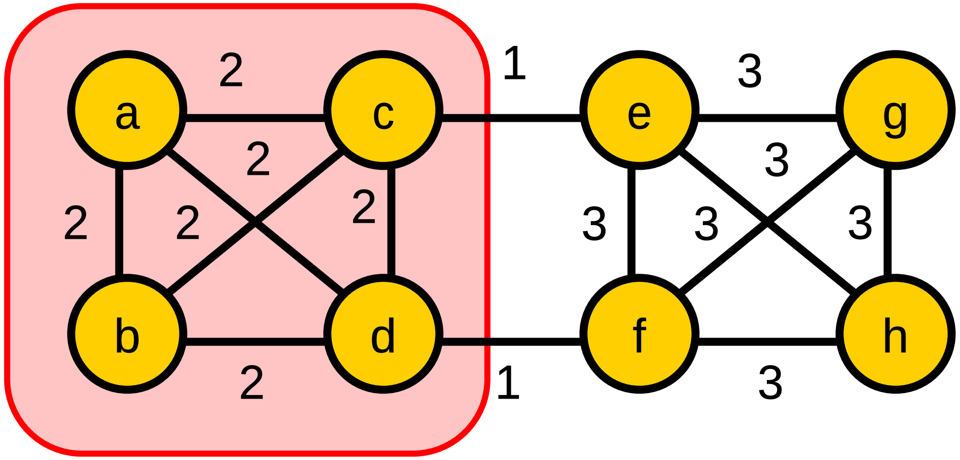
- F(A) is NOT always submodular

If X_i are all conditionally independent given Y,
then F(A) is submodular! [Krause & Guestrin `05]



Proof:
"information never hurts"

Another example: Cut functions

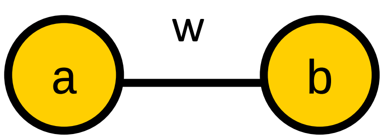


V={a,b,c,d,e,f,g,h}

$$F(A) = \sum_{s \in A, t \notin A} w_{s,t}$$

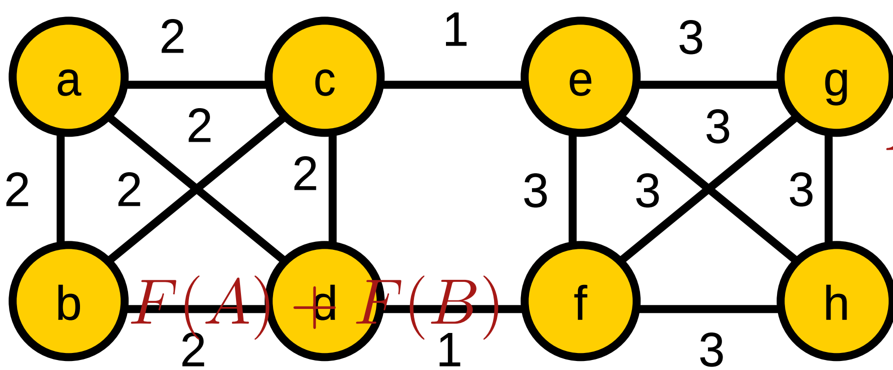
Cut function is submodular!

Why are cut functions submodular?



	S	$F_{ab}(S)$
$A \cap B$	{}	0
A	{a}	w
B	{b}	w
$A \cup B$	{a,b}	0

Submodular if w ≥ 0!



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

$$F(S) = \sum_{(i,j) \in E} \underbrace{F_{i,j}(S \cap \{i,j\})}_{\text{Cut function in subgraph } \{i,j\}}$$

Cut function in subgraph {i,j}

➔ Submodular!

Closedness under linear combinations

$F_1,\ldots,F_m$ submodular functions on V and $\lambda_1,\ldots,\lambda_m \geq 0$

Then: $F(A) = \sum_i \lambda_i F_i(A)$ is submodular

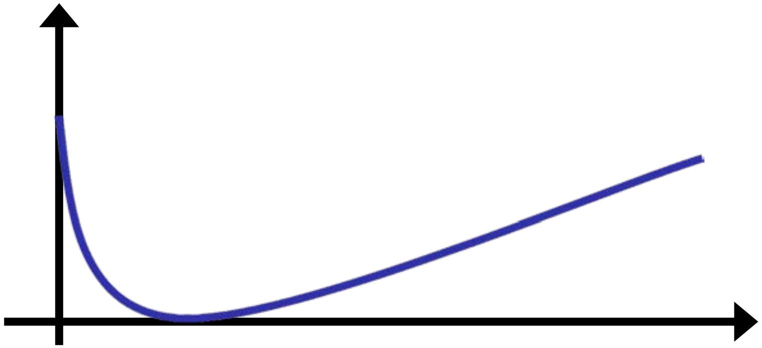
Submodularity closed under nonnegative linear combinations!

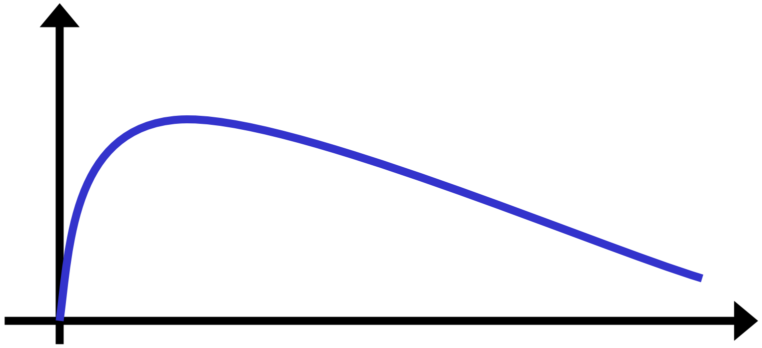
Extremely useful fact:

- $F_\theta(A)$ submodular ➔ $\sum_\theta P(\theta) F_\theta(A)$ submodular!
- Multicriterion optimization
- A basic proof technique! ☺

Submodularity …

discrete convexity ….

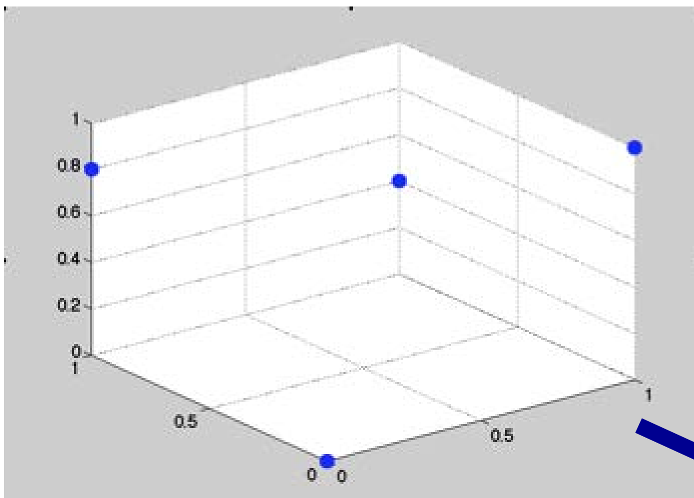


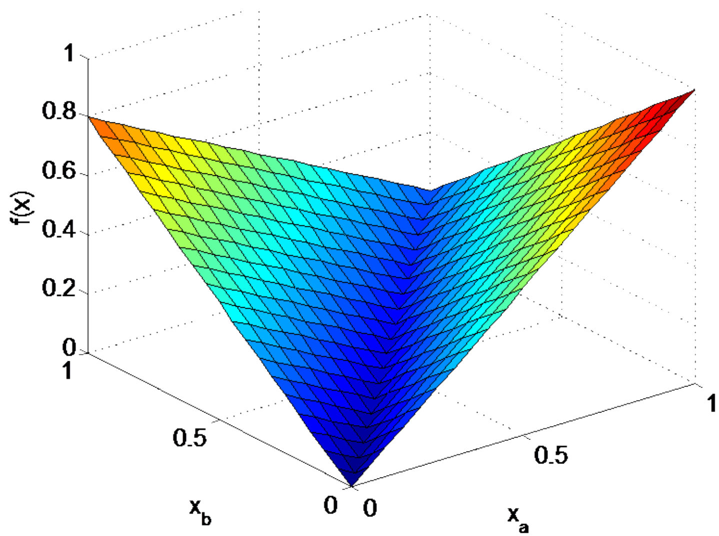


… or concavity?

Convex aspects

- convex extension
  - duality
  - efficient minimization





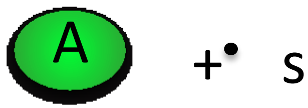
But this is only half of the story…

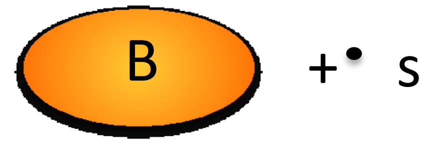
Concave aspects

- submodularity:

$$A \subseteq B, \quad s \notin B:$$

$$F(A \cup s) - F(A) \quad \geq \quad F(B \cup s) - F(B)$$

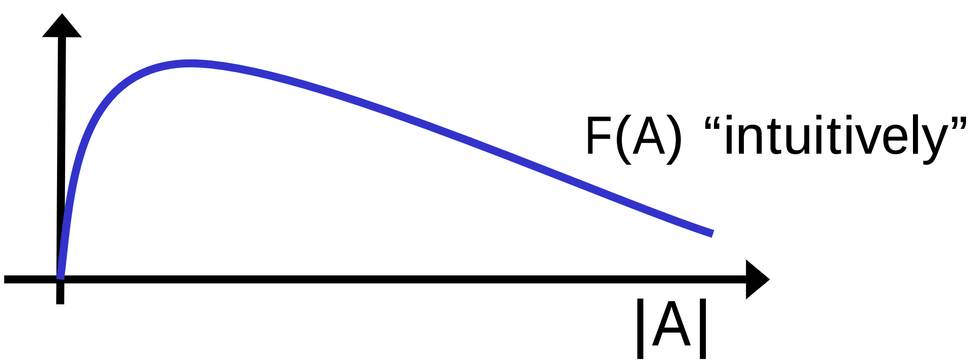




- concavity:

$$a \leq b, \quad s > 0:$$

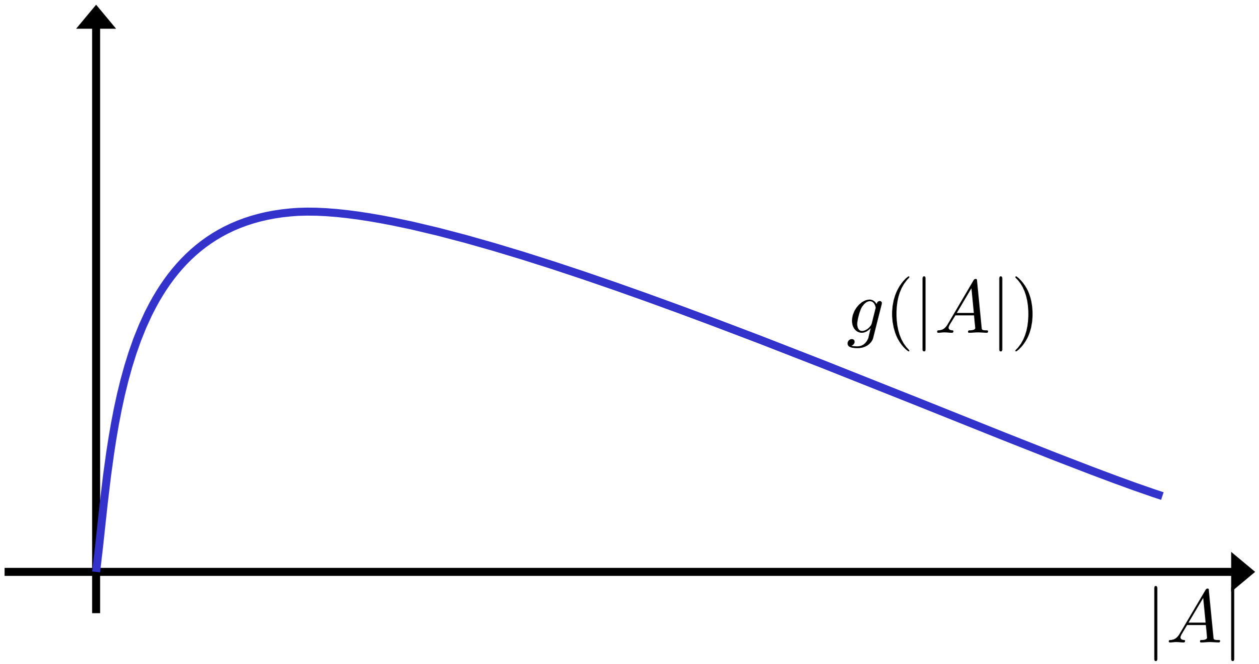
$$f(a+s) - f(a) \quad \geq \quad f(b+s) - f(b)$$



Submodularity and concavity

- suppose $g : \mathbb{N} \to \mathbb{R}$ and $F(A) = g(|A|)$

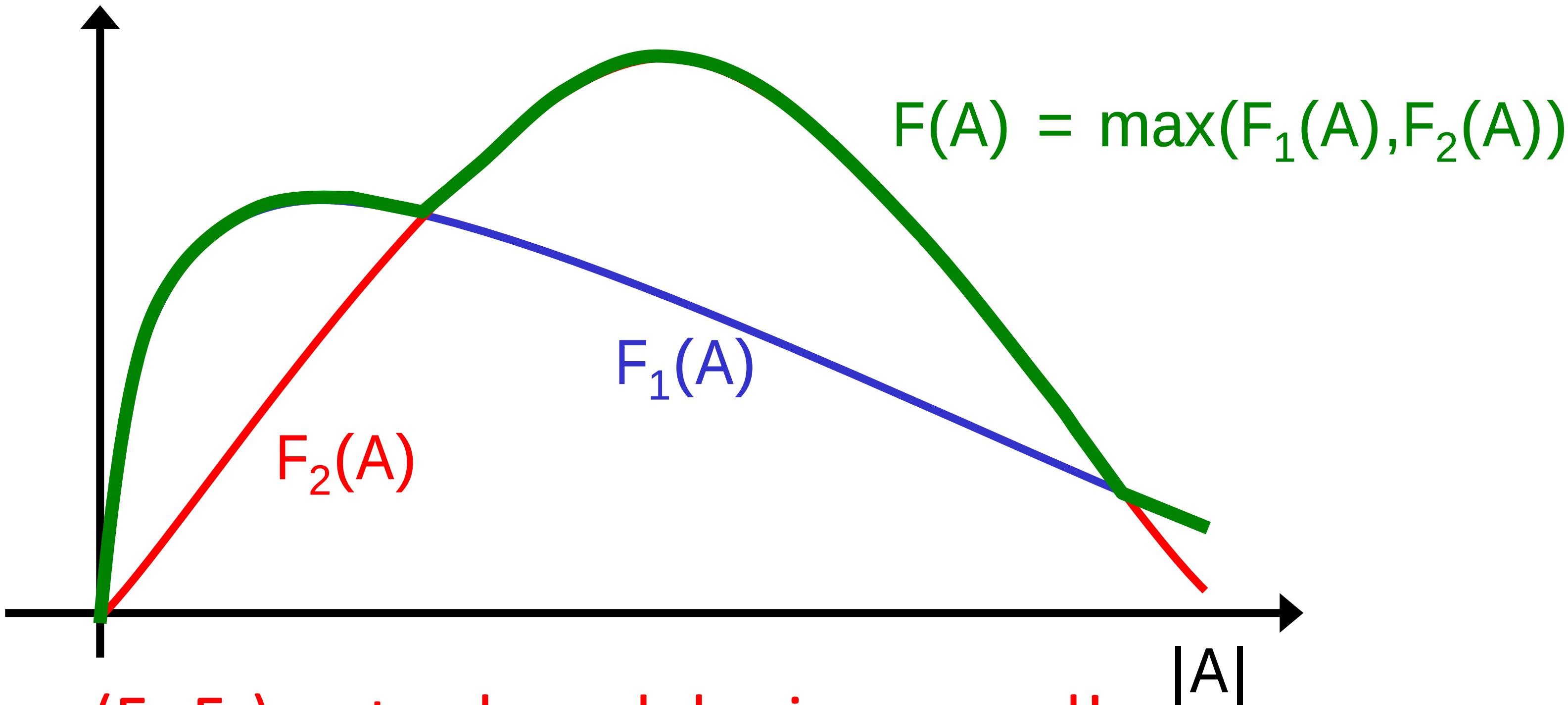
$F(A)$ submodular *if and only if* ... g is concave



Maximum of submodular functions

- $F_1(A), F_2(A)$ submodular. What about

$$F(A) = \max\{\, F_1(A), F_2(A) \,\} \quad ?$$



max(F_1,F_2) not submodular in general!

Minimum of submodular functions

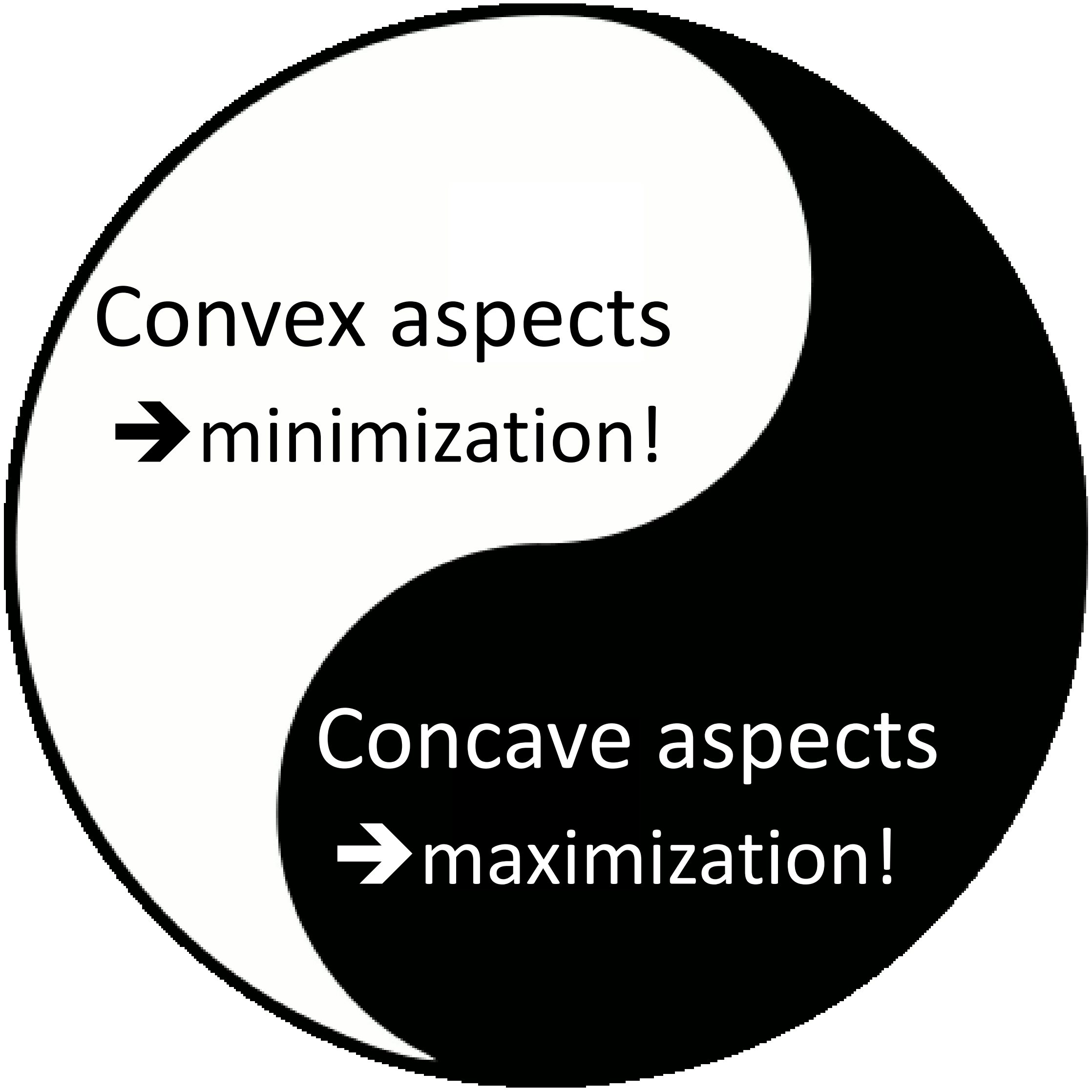
Well, maybe $F(A) = \min(F_1(A),F_2(A))$ instead?

	$F_1(A)$	$F_2(A)$
{}	0	0
{a}	1	0
{b}	0	1
{a,b}	1	1

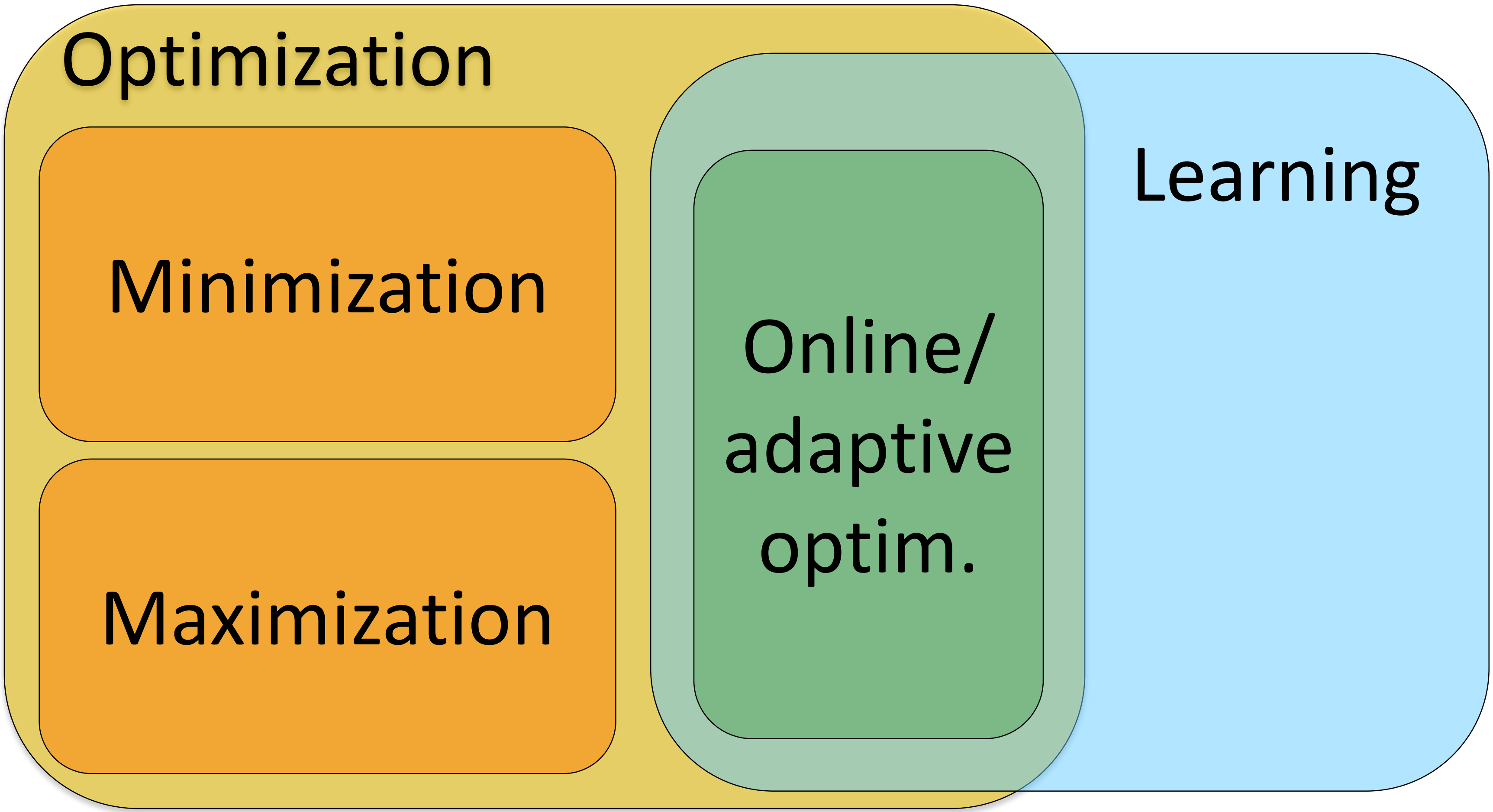
$$F(\{b\}) - F(\{\}) = 0$$
$$<$$
$$F(\{a,b\}) - F(\{a\}) = 1$$

$\min(F_1,F_2)$ not submodular in general!

Two faces of submodular functions



What to do with submodular functions



Here we focus on optimization & applications

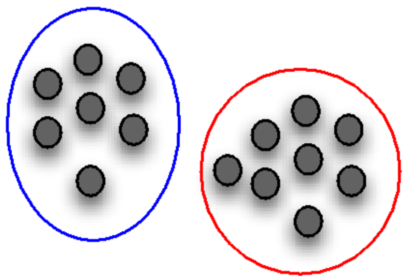
Optimization

Minimization

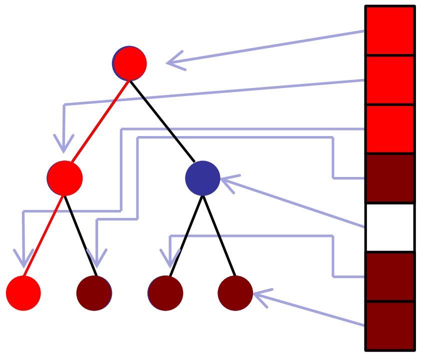
Maximization

Minimization and maximization not the same??

Submodular minimization

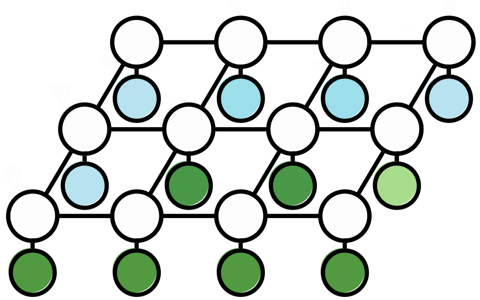


clustering

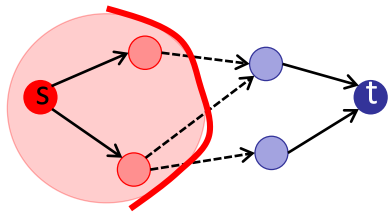


structured sparsity regularization

$$\min_{S \subseteq V} F(S)$$



MAP inference



minimum cut

Submodular minimization

$$\min_{S \subseteq V} F(S)$$

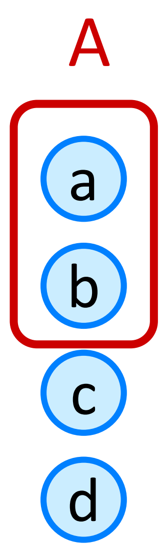
➔ submodularity and convexity

Set functions and energy functions

any set function

with $|V| = n$

$$F : 2^V \to \mathbb{R}$$

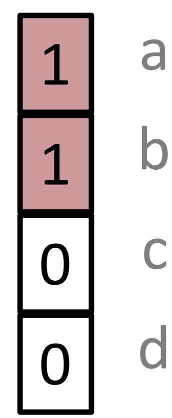


$$\hat{=}$$

... is a function on binary vectors!

$$F : \{0,1\}^n \to \mathbb{R}$$

$$x = e_A$$

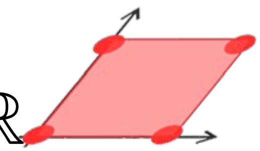


pseudo-boolean function

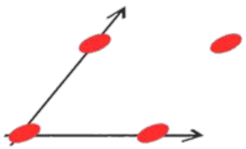
Submodularity and convexity

extension

$$f : [0,1]^n \to \mathbb{R}$$



$$F : \{0,1\}^n \to \mathbb{R}$$



Lovász extension

$$f(x) = \max_{y \in P_F} x \cdot y$$

convex

Lovász, 1982

- minimum of *f* is a minimum of F
- submodular minimization as convex minimization: polynomial time!

Grötschel, Lovász, Schrijver 1981

Submodularity and convexity

extension

$F : \{0,1\}^n \to \mathbb{R}$ $\longrightarrow$ $f : [0,1]^n \to \mathbb{R}$

Lovász extension

$$f(x) = \max_{y \in P_F} x \cdot y$$

convex

Lovász, 1982

- minimum of f is a minimum of F
- submodular minimization as convex minimization: polynomial time!

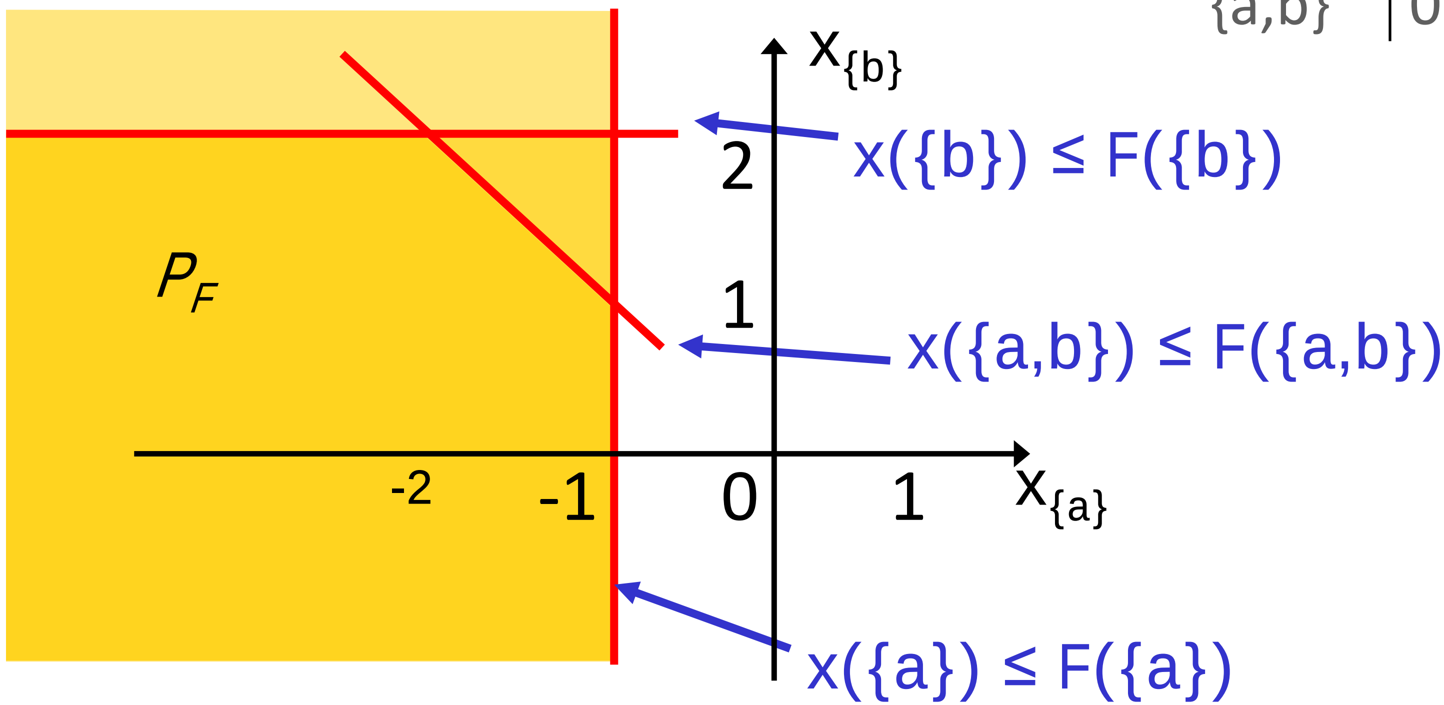
The submodular polyhedron P_F

$$P_F = \{x \in \mathbb{R}^n : x(A) \leq F(A) \text{ for all } A \subseteq V\}$$

$$x(A) = \sum_{i \in A} x_i$$

Example: V = {a,b}

A	F(A)
{}	0
{a}	-1
{b}	2
{a,b}	0



Evaluating the Lovász extension

$$P_F = \{x \in \mathbb{R}^n : x(A) \leq F(A) \text{ for all } A \subseteq V\}$$

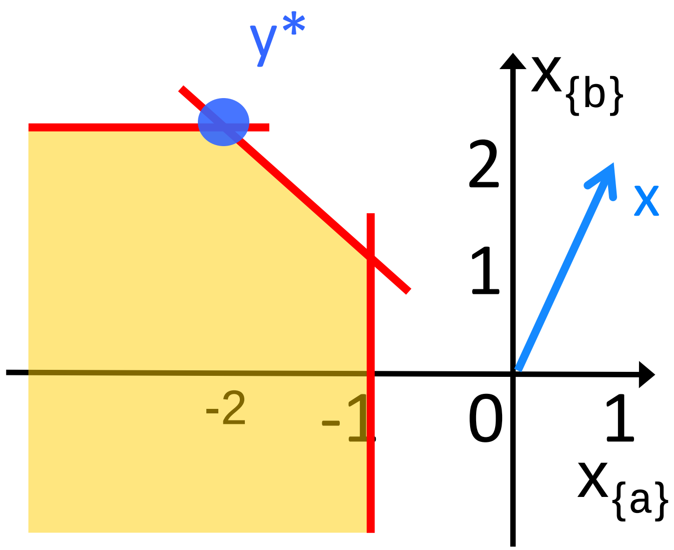
Linear maximization over P_F

$$f(x) = \max_{y \in P_F} x \cdot y$$

Exponentially many constraints!!! ☹

Computable in O(n log n) time ☺

[Edmonds '70]

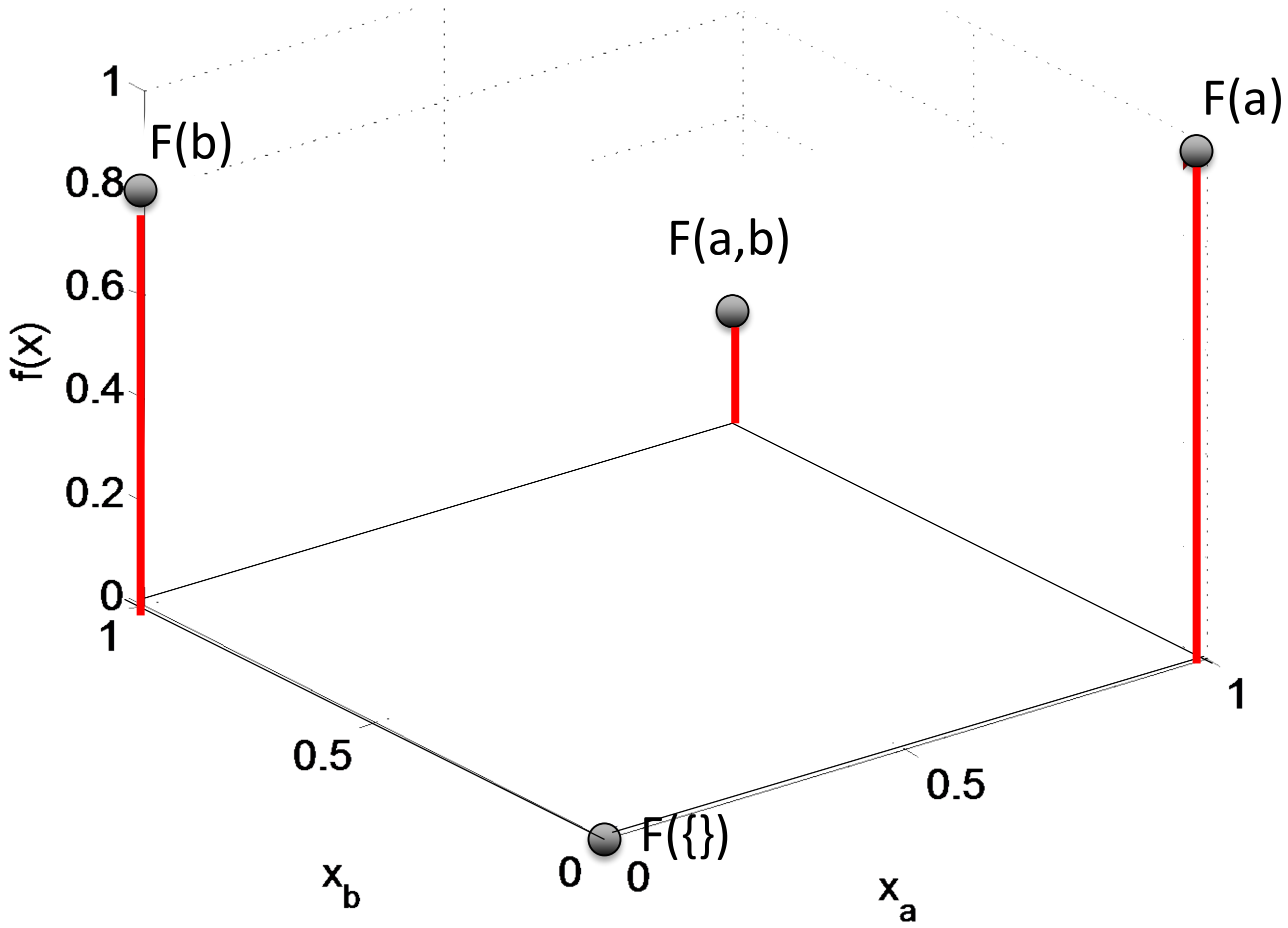


greedy algorithm:

- sort x
- order defines sets $S_i = \{1, \ldots, i\}$
- $y_i = F(S_i) - F(S_{i-1})$

- Subgradient
- Separation oracle

Lovász extension: example



A	F(A)
{}	0
{a}	1
{b}	.8
{a,b}	.2

Submodular minimization

$$\min_{A \subseteq V} F(A)$$

minimize convex extension

- ellipsoid algorithm
  [Grötschel et al. `81]
- subgradient method, smoothing [Stobbe & Krause `10]
- duality: minimum norm point algorithm
  [Fujishige & Isotani '11]

combinatorial algorithms

- Fulkerson prize
  Iwata, Fujishige, Fleischer '01 & Schrijver '00
- state of the art:
  $O(n^4T + n^5 \log M)$ [Iwata '03]
  $O(n^6 + n^5T)$ [Orlin '09]

T = time for evaluating *F*

The minimum-norm-point algorithm

Example: V = {a,b}

A	F(A)
{}	0
{a}	-1
{b}	2
{a,b}	0

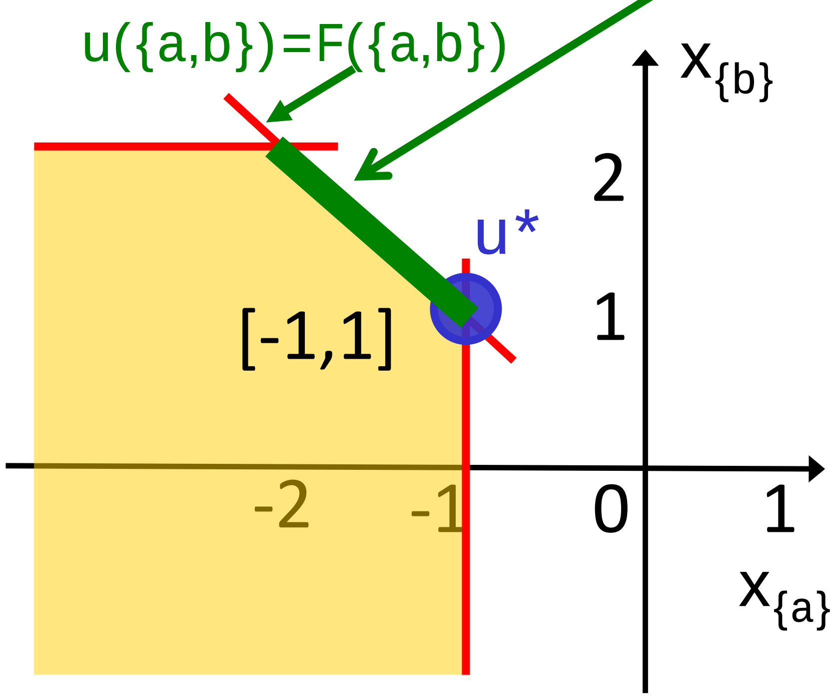
Regularized problem

$$\min_{x} f(x) + \frac{1}{2}\|x\|^2$$

dual: minimum norm problem

$$u^* = \arg\min_{u \in B_F} \frac{1}{2}\|u\|^2$$

Base polytope B_F



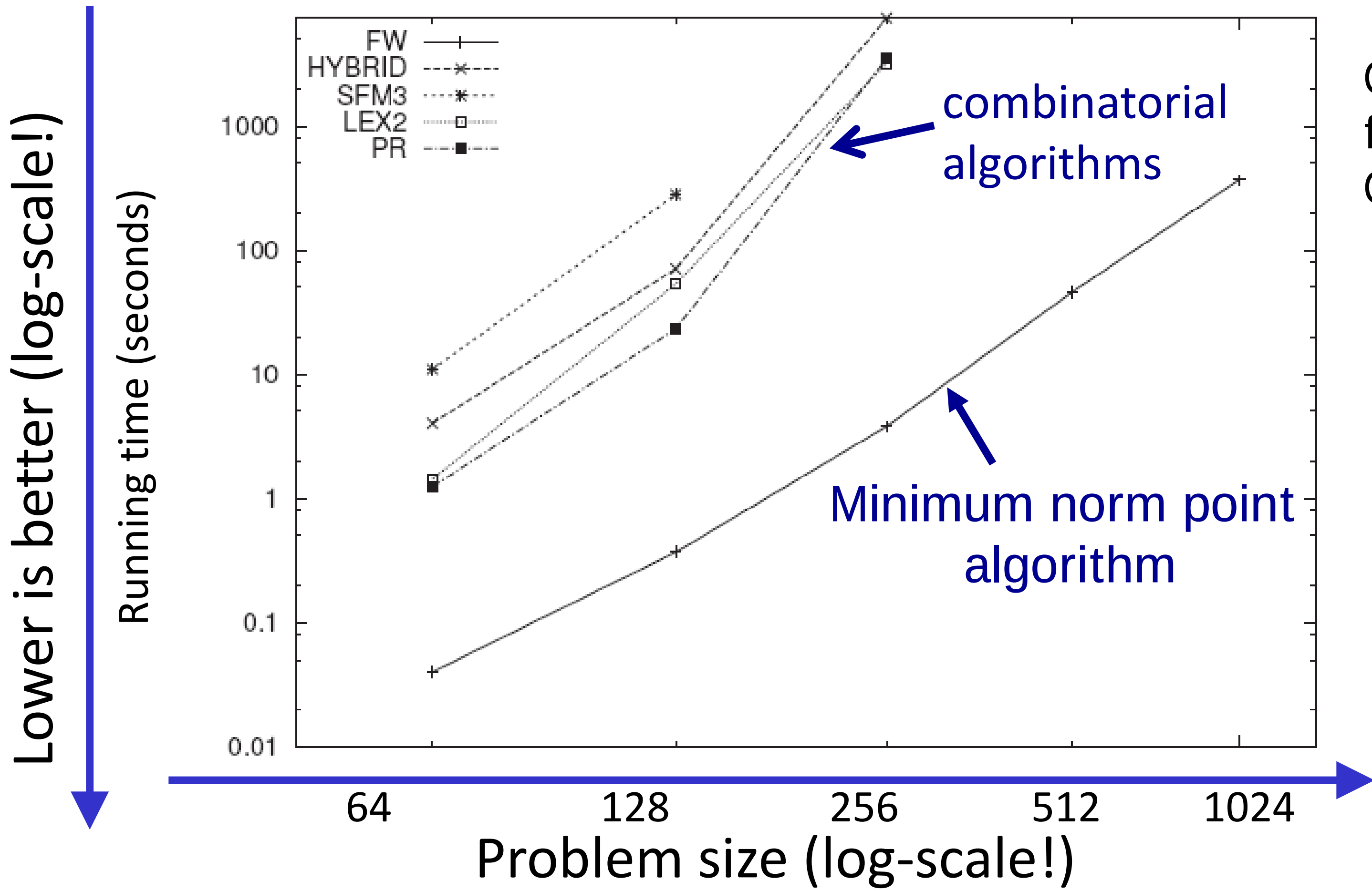
$$A^* = \{i \mid u^*(i) \leq 0\}$$

minimizes *F*:

$$A^* = \arg\min_{A \subseteq V} F(A)$$

Fujishige '91, Fujishige & Isotani '11

Empirical comparison

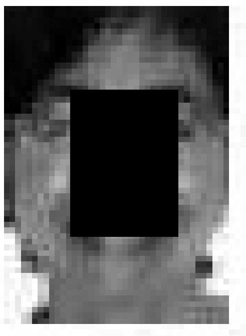


Cut functions from DIMACS Challenge

Minimum norm point algorithm: usually orders of magnitude faster

[Fujishige & Isotani '11]

Example I: Sparsity



$\approx .1$

$+ .4$

$+ .2$

$$y \approx Mx$$

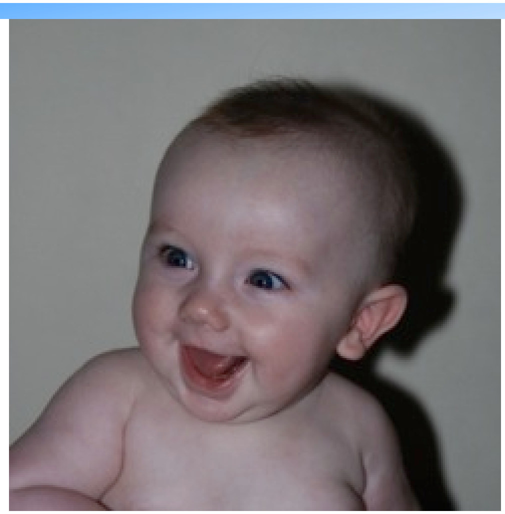
Want „representative“ dictionaries

Want „simple“ explanations (e.g., use few columns of M)

Example I: Sparsity

d

pixels

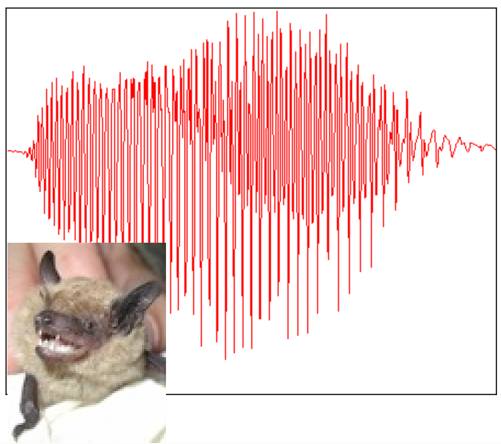


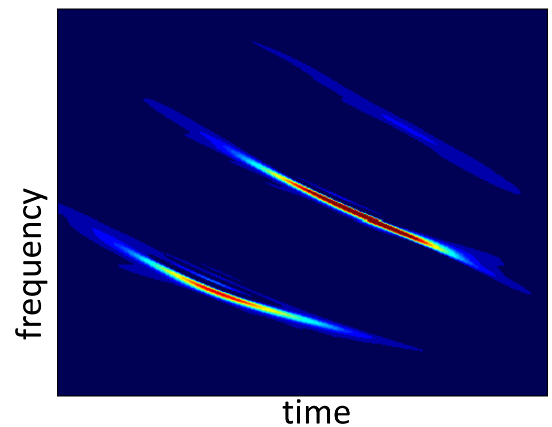
$k \ll d$

large
wavelet
coefficients

d

wideband
signal
samples





$k \ll d$

large
Gabor (TF)
coefficients

Many natural signals sparse in suitable basis.
Can exploit for learning/regularization/compressive sensing...

Sparse reconstruction

$$\min_x \; \|y - Mx\|^2 \quad + \lambda \Omega(x)$$

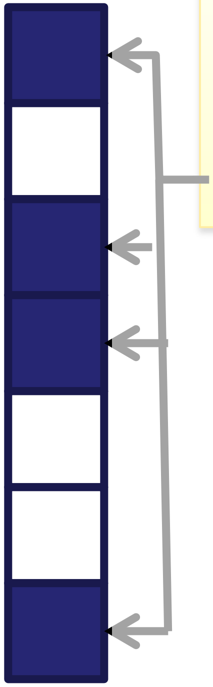
explain *y* with few columns of *M*: few x_i

discrete regularization on support *S* of *x*

$$\Omega(x) = \|x\|_0 \quad = |S|$$

relax to convex envelope

$$\Omega(x) = \|x\|_1$$



subset selection: S = {1,3,4,7}

in nature: sparsity pattern often not random…

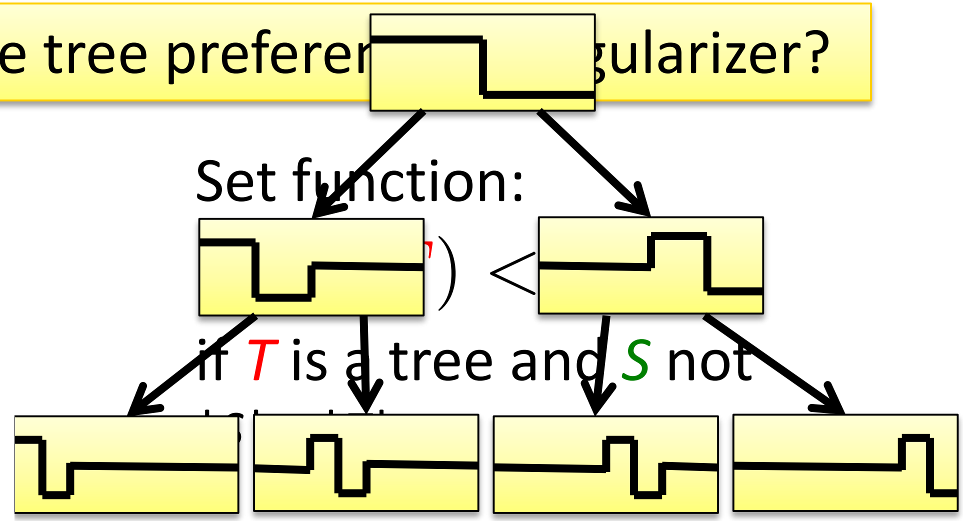
Structured sparsity

Incorporate tree preferen… …gularizer?

Set function:

) <

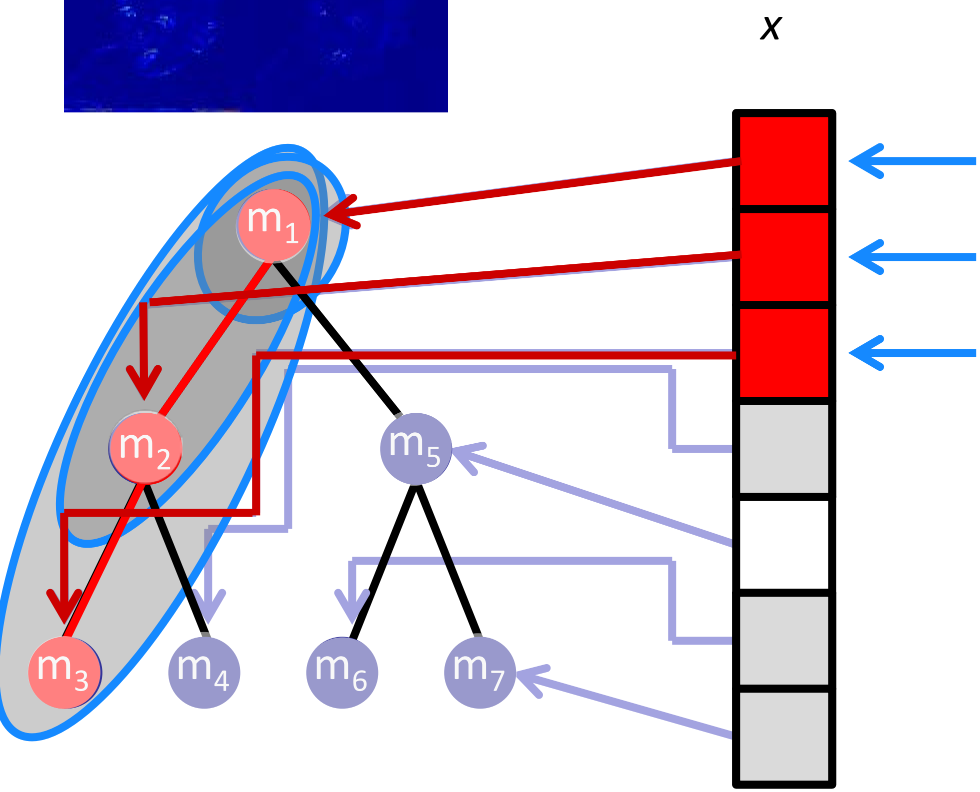
if T is a tree and S not



$$F(S) = \left| \bigcup_{s \in S} \text{ancestors}(s) \right|$$

Structured sparsity

Incorporate tree preference in regularizer?



Set function:

$$F(T) < F(S)$$

If T is a tree and S not,

$|S| = |T|$

$$F(S) = \left| \bigcup_{s \in S} \text{ancestors}(s) \right|$$

$$F(T) = 3$$

Structured sparsity

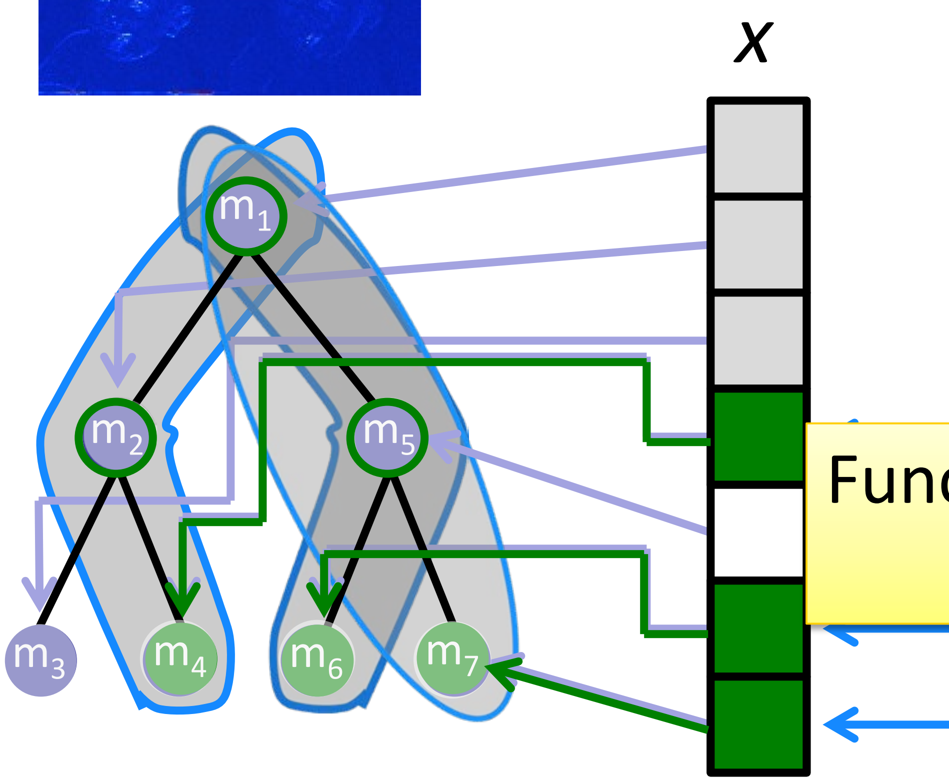
Incorporate tree preference in regularizer?

Set function:

$$F(T) < F(S)$$

If T is a tree and S not,

$|S| = |T|$



Function F is …

submodular! ☺

$$F(T) = 3$$

Sparsity-inducing norms through submodular functions [Bach NIPS 2010]

$$\min_{x} \; \|y - Mx\|^2 \quad + \lambda\Omega(x)$$

explain y with few columns of M: few x_i

prior knowledge: patterns of nonzeros

discrete regularization on support S of x

$$\Omega(x) = \|x\|_0 \quad = |S|$$

submodular function

$$\Omega(x) = F(S)$$

relax to convex envelope

$$\Omega(x) = \|x\|_1$$

→ Lovász extension

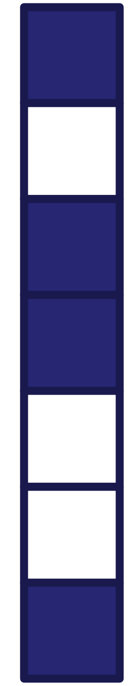
$$\Omega(x) = f(|x|)$$

Optimization: submodular minimization

Further connections: Dictionary Selection

$$\min_x \|y - Mx\|^2 + \lambda\Omega(x)$$

Where does the dictionary M come from?

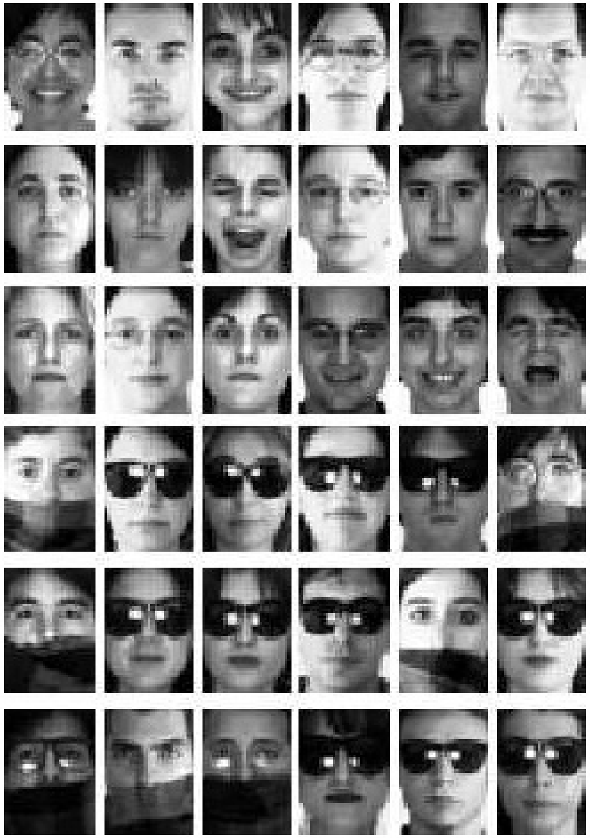


Want to learn it from data: $\{y_1, \ldots, y_n\} \subseteq \mathbb{R}^d$

Selecting a dictionary with near-max. variance reduction
⇔ Maximization of approximately submodular function

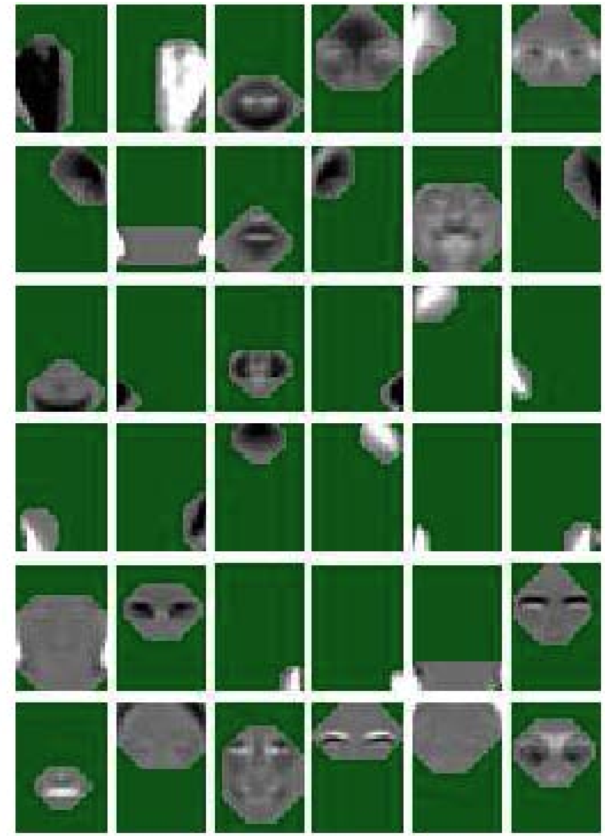
[Krause & Cevher '10; Das & Kempe '11]

Structured sparse dictionary learning [Bach et al, 2011]



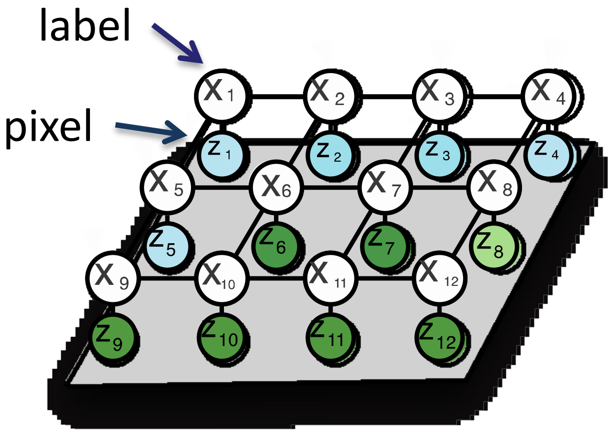
Original images

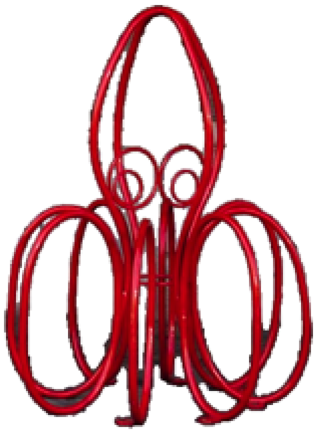
Dictionary from NMF



Structured-sparse Dictionary (SSPCA)

Example II: MAP inference





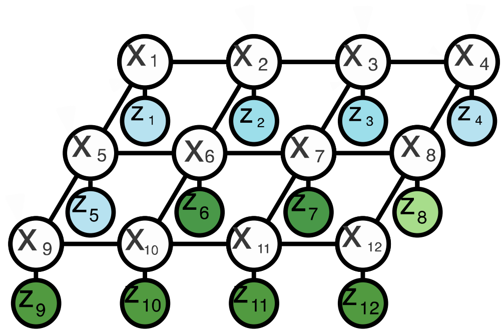
$$\max_{\mathbf{x}\in\{0,1\}^n} \; P(\mathbf{x} \mid \mathbf{z}) \propto \exp(-E(\mathbf{x};\mathbf{z}))$$

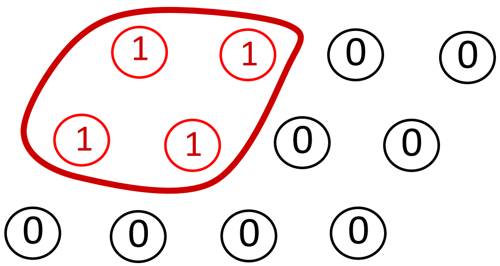
labels

pixel values

$$\Leftrightarrow \quad \min_{\mathbf{x}\in\{0,1\}^n} \; E(\mathbf{x};\mathbf{z})$$

Example II: MAP inference



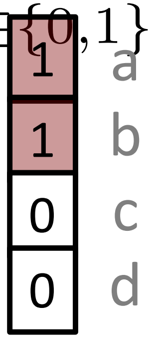


Recall: equivalence

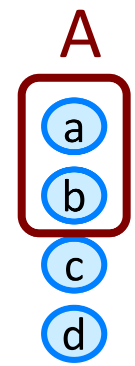
function on binary vectors | set function

$$\max_{\mathbf{x}\in\{0,1\}^n} P(\mathbf{x} \mid \mathbf{z}) \propto \exp(-E(\mathbf{x};\mathbf{z}))$$

$x = e_A$



$$E(e_A;\mathbf{z}) \quad = \quad F(A)$$



if F is submodular, then

$$\Leftrightarrow \quad \min_{\mathbf{x}\in\{0,1\}^n} E(\mathbf{x};\mathbf{z})$$

MAP inference = submodular minimization!

polynomial-time

Special cases

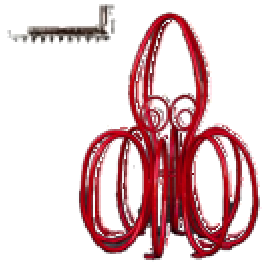
Minimizing general submodular functions:

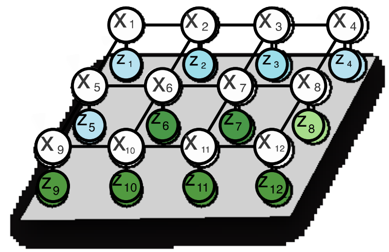
poly-time, but not very scalable

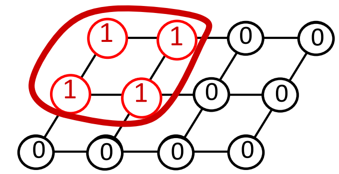
Special structure $\rightarrow$ faster algorithms

- Symmetric functions
- Graph cuts
- Concave functions
- Sums of functions with bounded support
- ...

MAP inference







$$\min_{\mathbf{x}\in\{0,1\}^n} E(\mathbf{x};\mathbf{z}) = \sum_i E_i(x_i) + \sum_{ij} E_{ij}(x_i, x_j) \quad \equiv \min_{A\subseteq V} F(A)$$

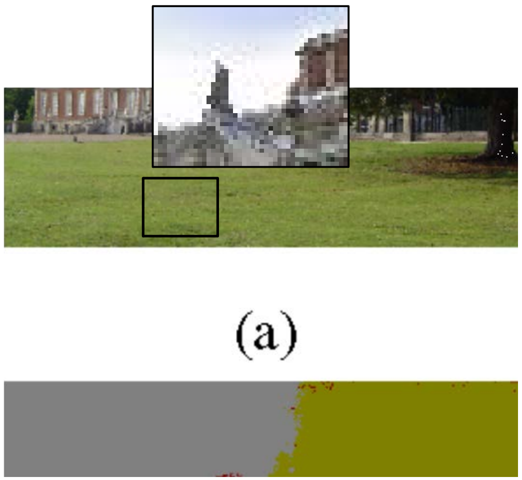
if each E_{ij} is submodular (“attractive”):

$$\underset{a}{E_{ij}(1,0)} + \underset{b}{E_{ij}(0,1)} \;\geq\; E_{ij}(0,0) + \underset{ab}{E_{ij}(1,1)}$$

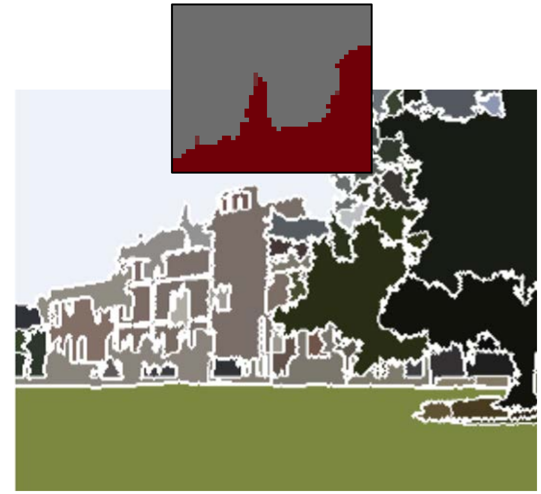
then F is a graph cut function.

MAP inference = Minimum cut: fast ☺

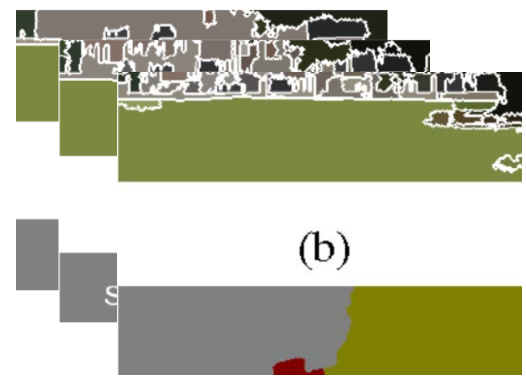
Pairwise is not enough…



color + pairwise



color + pairwise +



Pixels in one tile should have the same label

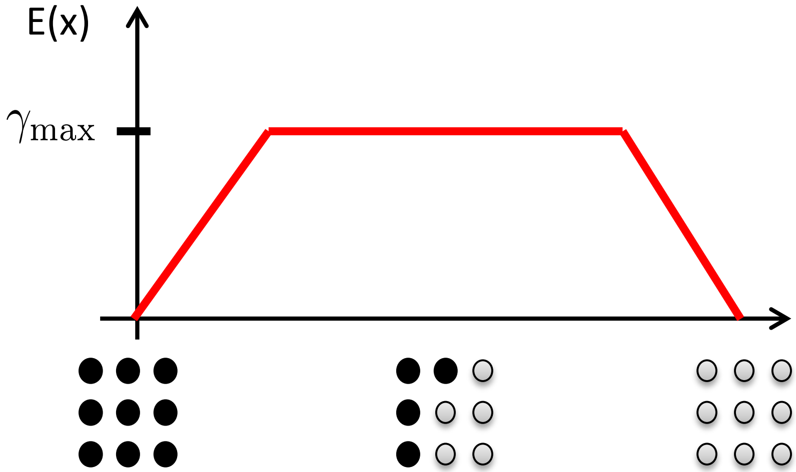
$$E(x) = \sum_i E_i(x_i) + \sum_{ij} E_{ij}(x_i, x_j)$$

[Kohli et al.`09]

Enforcing label consistency

Pixels in a superpixel should have the same label

(b)



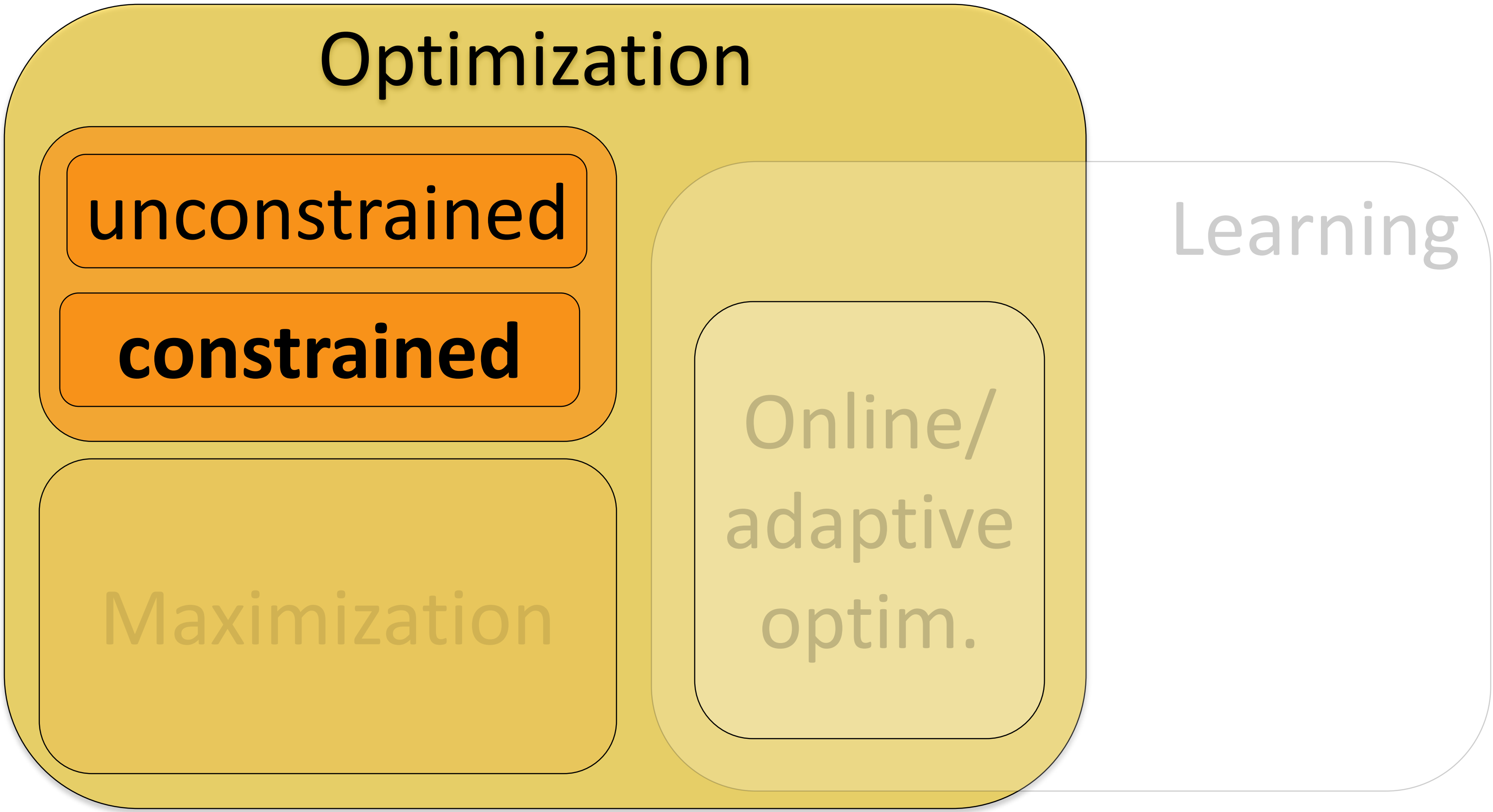
concave function of cardinality ➔ submodular ☺

Can still be transformed into a graph cut instance!

Other special cases

- Symmetric: $F(S) = F(V \setminus S)$
  - Queyranne's algorithm: $O(n^3)$ [Queyranne, 1998]
- Concave of modular: $$F(S) = \sum_i g_i\Big(\sum_{s \in S} w(s)\Big)$$
  [Stobbe & Krause `10, Kohli et al, `09]
- Sum of submodular functions, each bounded support
  [Kolmogorov `12]

Submodular minimization



Submodular minimization

- unconstrained: $\min\ F(A) \quad \text{s.t. } A \subseteq V$
  - nontrivial algorithms, polynomial time

special case: balanced cut

- constraints: e.g. $\min\ F(A) \quad \text{s.t. } |A| \geq k$
  - limited cases doable: odd/even cardinality, inclusion/exclusion of a set $\ldots$

General case: NP hard

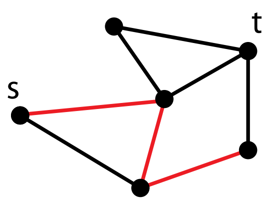
- hard to approximate within polynomial factors!
- But: special cases often still work well

[Lower bounds: Goel et al.`09, Iwata & Nagano `09, Jegelka & Bilmes `11]

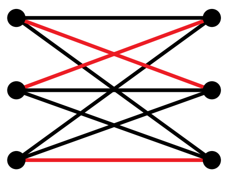
Constraints

minimum…

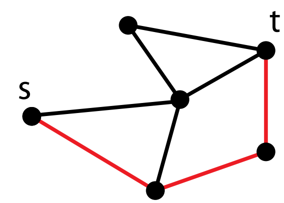
cut



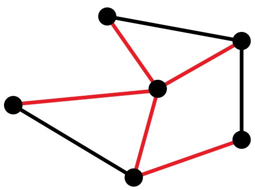
matching



path



spanning tree



ground set: edges in a graph

$$\min_{S \in \mathcal{C}} \sum_{e \in S} w(e) \quad \Longrightarrow \quad \min_{S \in \mathcal{C}} F(S)$$

Constrained modular minimization

Constrained submodular minimization

Submodular (“cooperative”) cut
[Jegelka & Bilmes CVPR ‘11]

Graph cut

Efficient constrained optimization

Idea: minimize a series of modular surrogate functions

1. compute linear upper bound $\widehat{F}^i(S^i) = F(S^i)$

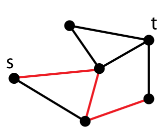
$$\hat{F}^i(S) = \sum_{e \in S} w^i(S)$$

2. Solve easy sum-of-weights (modular) problem:

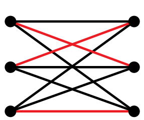
$$S^i = \arg\min_{S \in \mathcal{C}} \hat{F}^i(S)$$

and repeat.

cut

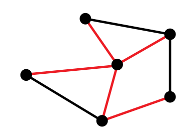


matching

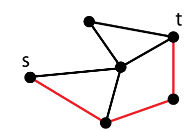


- efficient
- only need to solve sum-of-weights problems
- Provides certain approximation guarantees

spanning tree



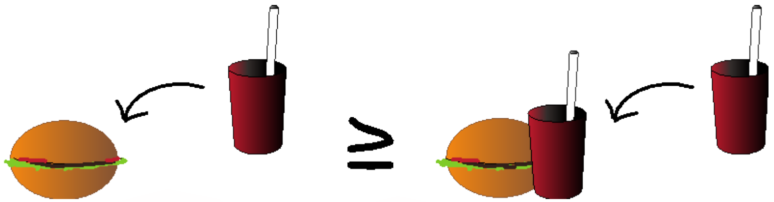
path

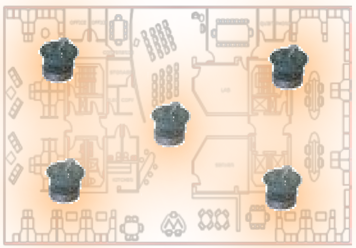


[Jegelka & Bilmes `11, Iyer et al. ICML `13, see also Krause et al ‘06]

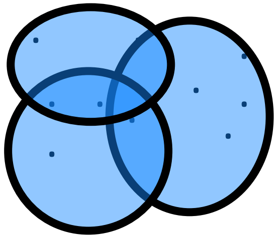
Outline

- What is submodularity?
- Optimization
  - Minimize costs
  - **Maximize utility**
- Applications
- Outlook and pointers

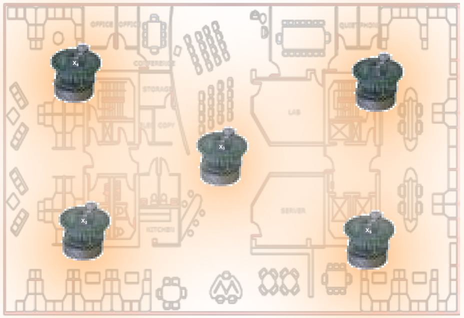




Submodular maximization

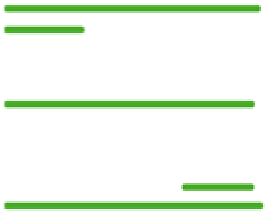


covering

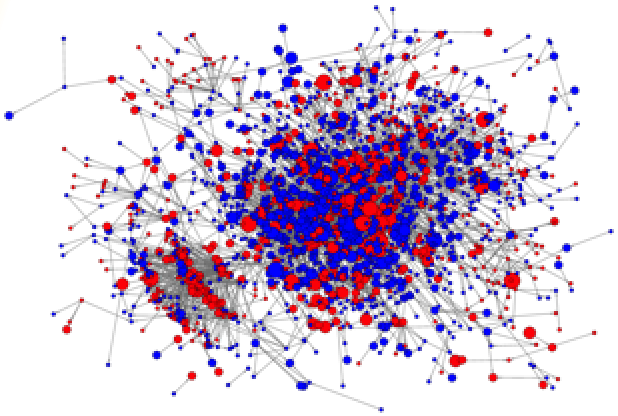


sensing

$$\max_{S \subseteq V} F(S)$$

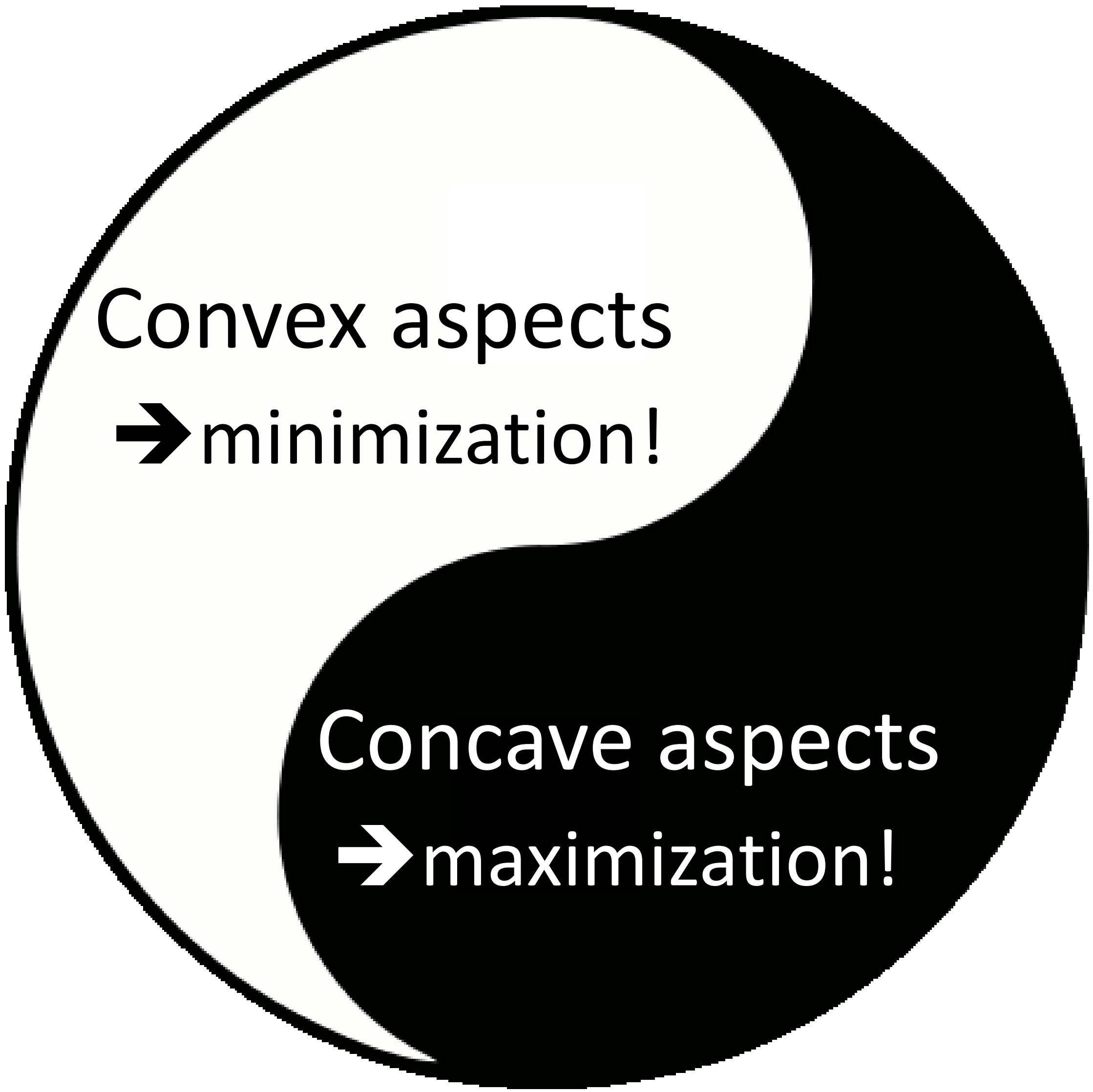


summarization



network inference

Two faces of submodular functions



Submodular maximization

$$\max_{S \subseteq V} F(S)$$

➔ submodularity and concavity

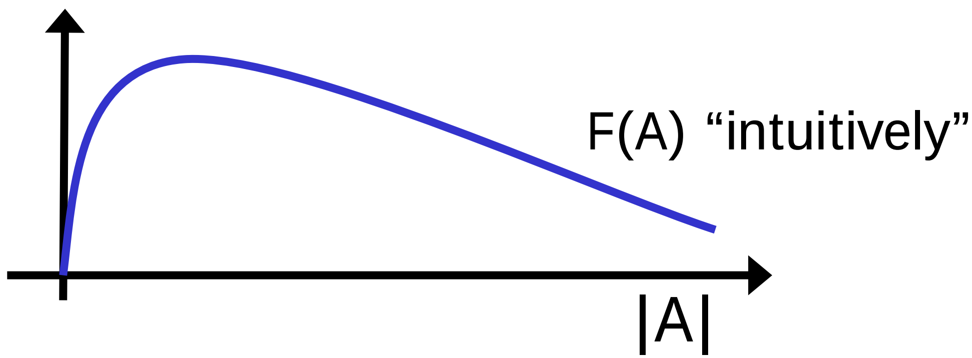
Concave aspects

- submodularity:

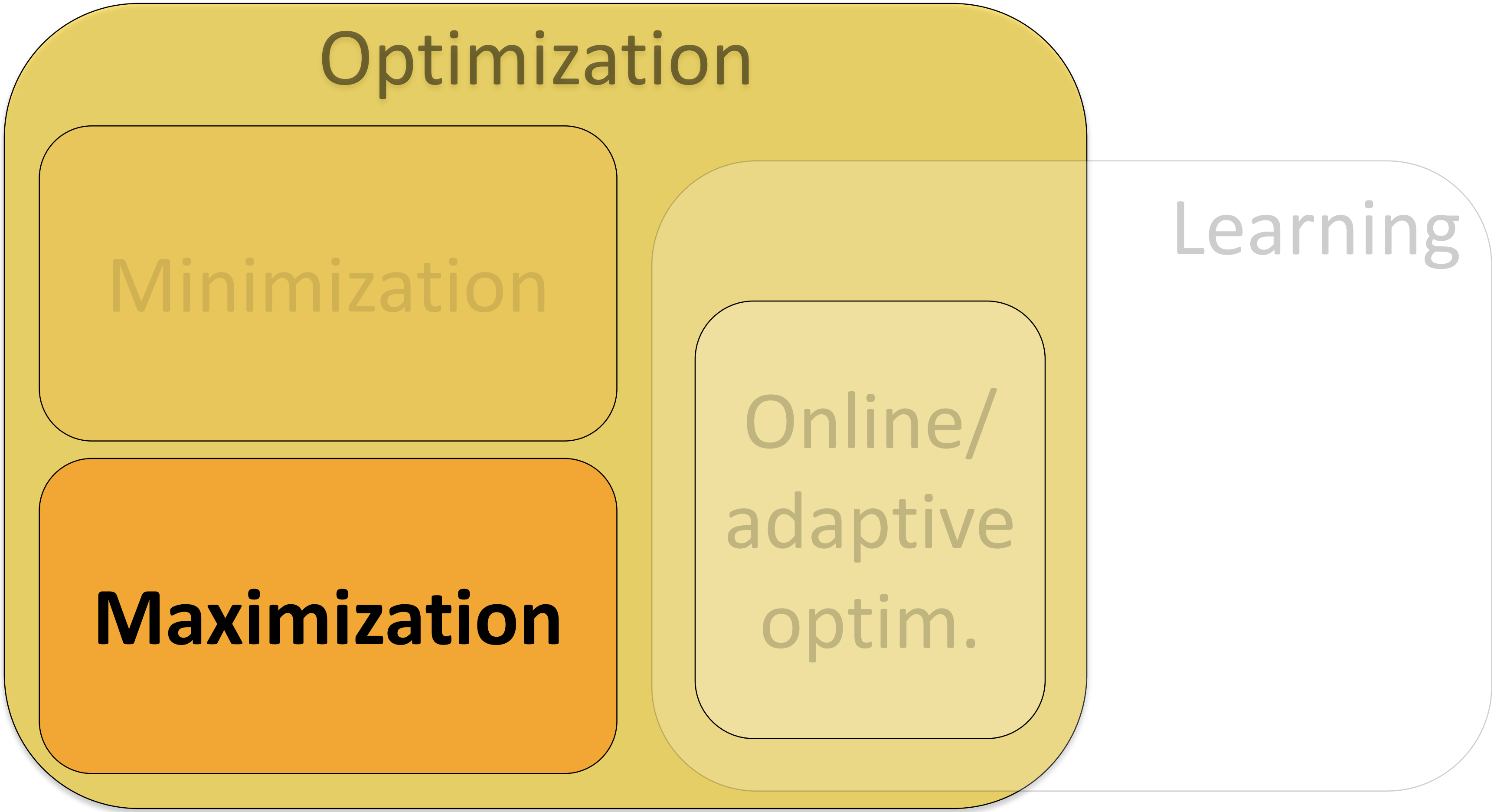
$$A \subseteq B, \;\; s \notin B :$$
$$F(A \cup s) - F(A) \quad \geq \quad F(B \cup s) - F(B)$$

- concavity:

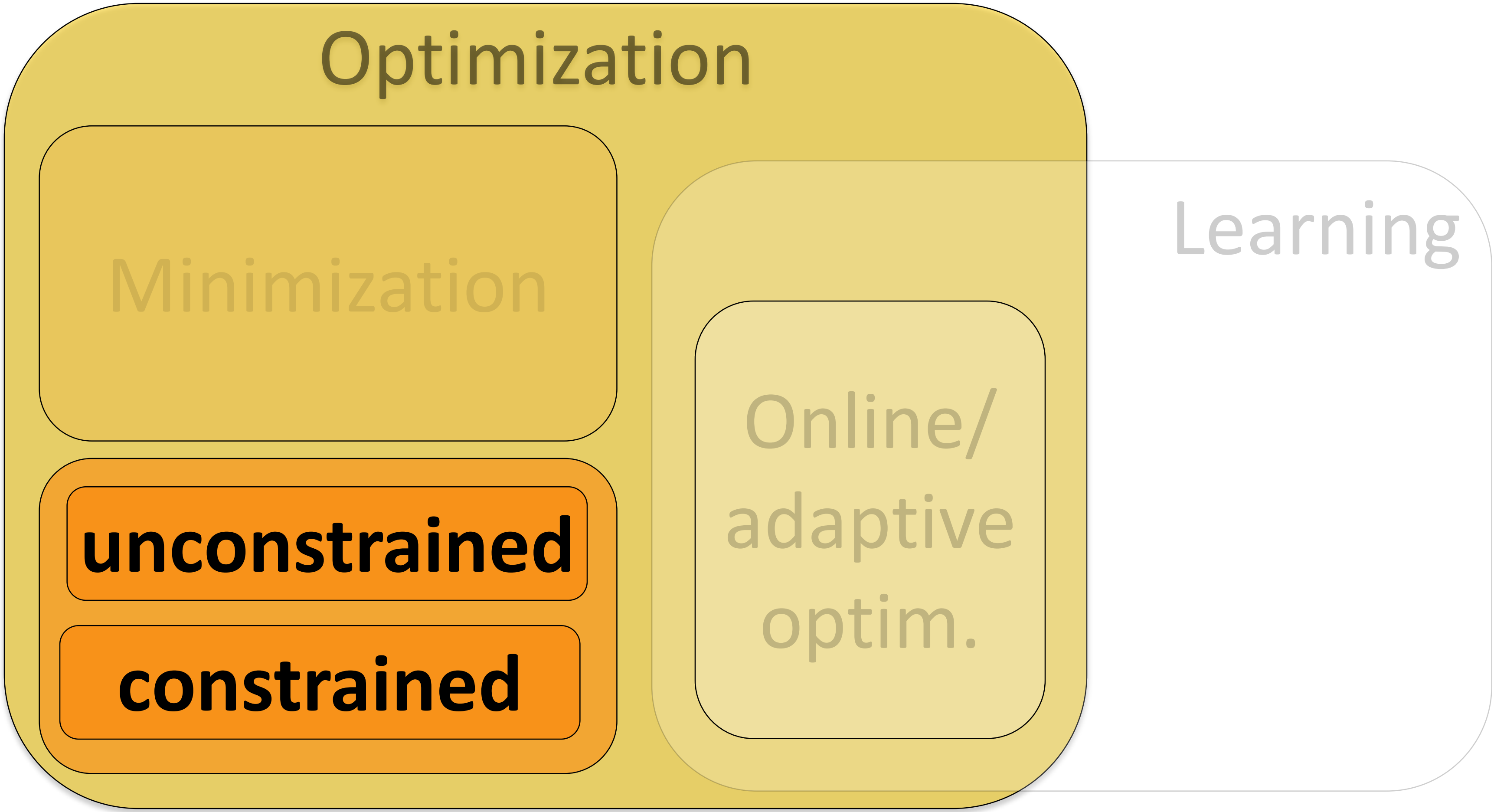
$$a \leq b, \;\; s > 0 :$$
$$f(a+s) - f(a) \quad \geq \quad f(b+s) - f(b)$$



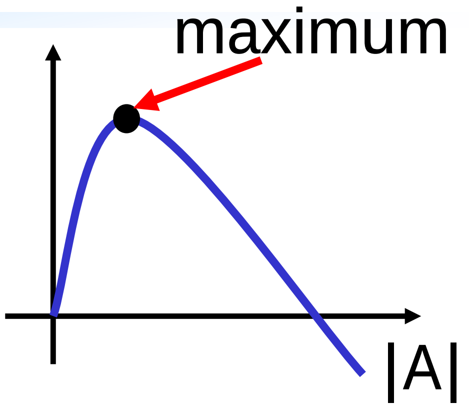
Optimization



Optimization



Maximizing submodular functions



- Suppose we want for submodular F

$$A^* = \arg\max_A F(A) \text{ s.t. } A \subseteq V$$

- Example:
  - F(A) = U(A) – C(A) where U(A) is submodular utility, and C(A) is supermodular cost function

- In general: NP hard. Moreover:
- If F(A) can take negative values:
  As hard to approximate as maximum independent set (i.e., NP hard to get $O(n^{1-\varepsilon})$ approximation)

Exact maximization of SFs

- Mixed integer programming
  - Series of mixed integer programs [Nemhauser et al ‘81]
  - Constraint generation [Kawahara et al ‘09]
- Branch-and-bound
  - „Data-Correcting Algorithm“ [Goldengorin et al ’99]

Useful for small/moderate problems

All algorithms worst-case exponential!

Maximizing positive submodular functions

[Feige, Mirrokni, Vondrak '09; Buchbinder, Feldman, Naor, Schwartz '12]

Theorem

Given a nonnegative submodular function F,
RandomizedUSM returns set A_R such that

$$F(A_R) \geq 1/2 \ \max_A F(A)$$

- Cannot do better in general than ½ unless P = NP

Unconstrained vs. constraint maximization

Given monotone utility F(A) and cost C(A), optimize:

Option 1:

$$\boxed{\begin{aligned} &\max_A F(A) - C(A) \\ &\text{s.t.}\quad A \subseteq V \end{aligned}}$$

"Scalarization"

Option 2:

$$\boxed{\begin{aligned} &\max_A F(A) \\ &\text{s.t.}\quad C(A) \leq B \end{aligned}}$$

"Constrained maximization"

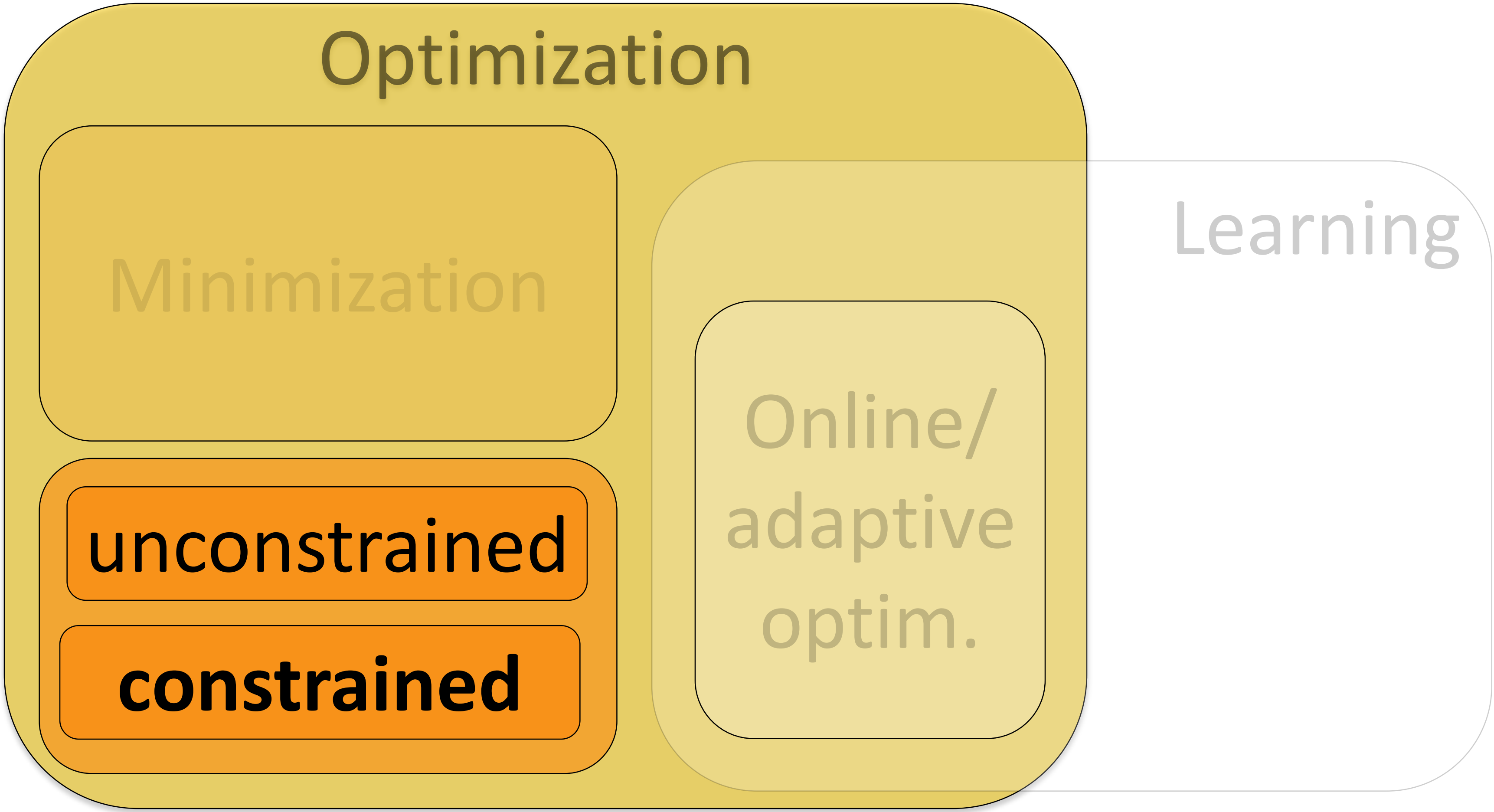
Can get 1/2 approx…

if F(A)-C(A) ≥ 0 for all sets A

Positiveness is a strong requirement ☹

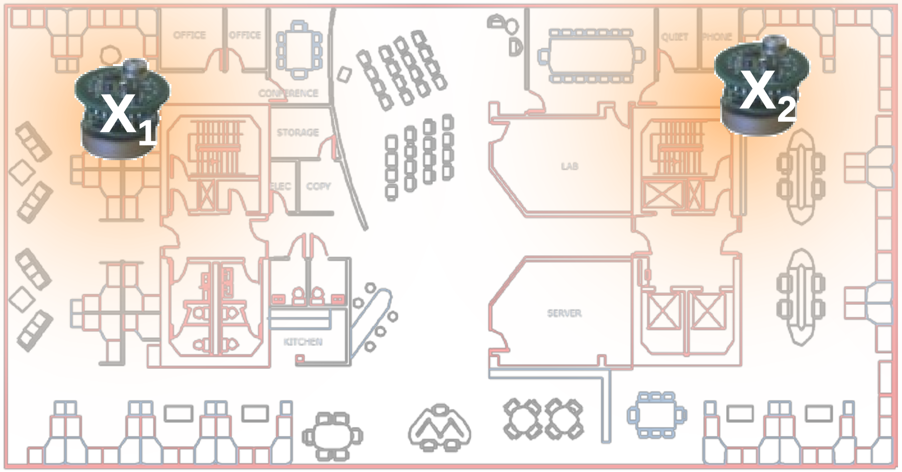
What is possible?

Optimization

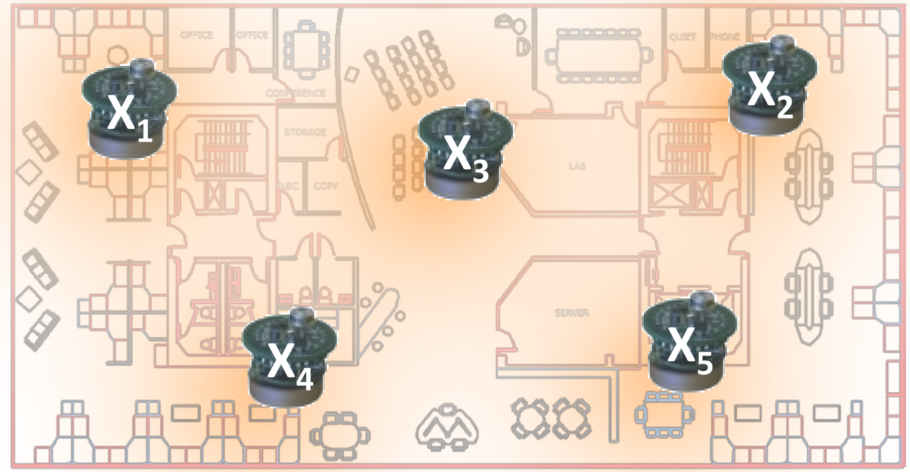


Monotonicity

Placement A = {1,2}



Placement B = {1,…,5}



F is monotonic: $$\forall A, s : \underbrace{F(A \cup \{s\}) - F(A)}_{\Delta(s \mid A)} \geq 0$$

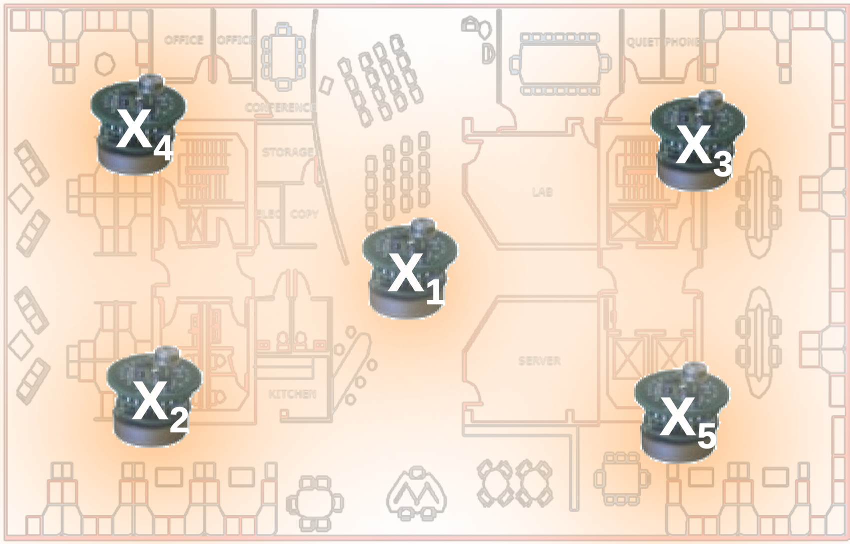
$$\Delta(s \mid A) \geq 0$$

Adding sensors can only help

Cardinality constrained maximization

- **Given**: finite set V, monotone submodular F
- **Want**: $\mathcal{A}^* \subseteq \mathcal{V}$ such that
$$\mathcal{A}^* = \operatorname*{argmax}_{|\mathcal{A}|\leq k} F(\mathcal{A})$$

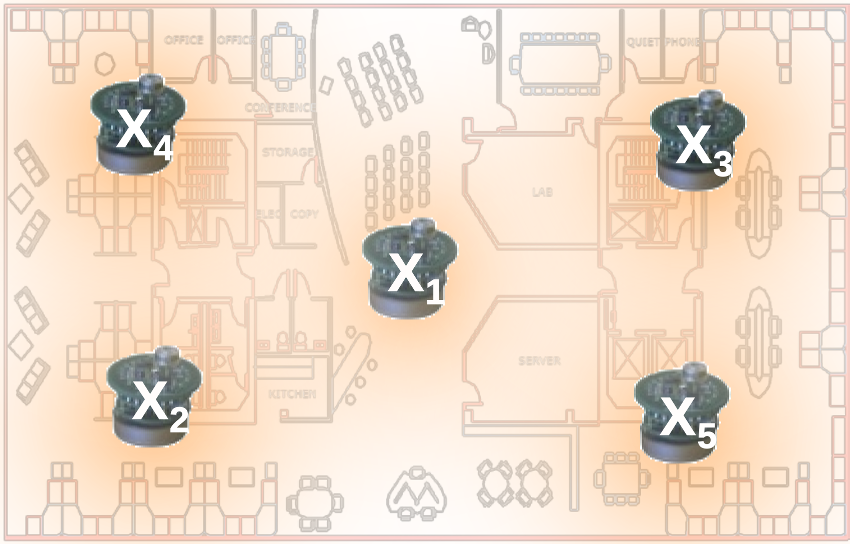
NP-hard!



Greedy algorithm

- **Given**: finite set V, monotone submodular F
- **Want**: $\mathcal{A}^* \subseteq \mathcal{V}$ such that $\mathcal{A}^* = \operatorname{argmax}_{|\mathcal{A}| \leq k} F(\mathcal{A})$

NP-hard!



Greedy algorithm:

Start with $\mathcal{A} = \emptyset$

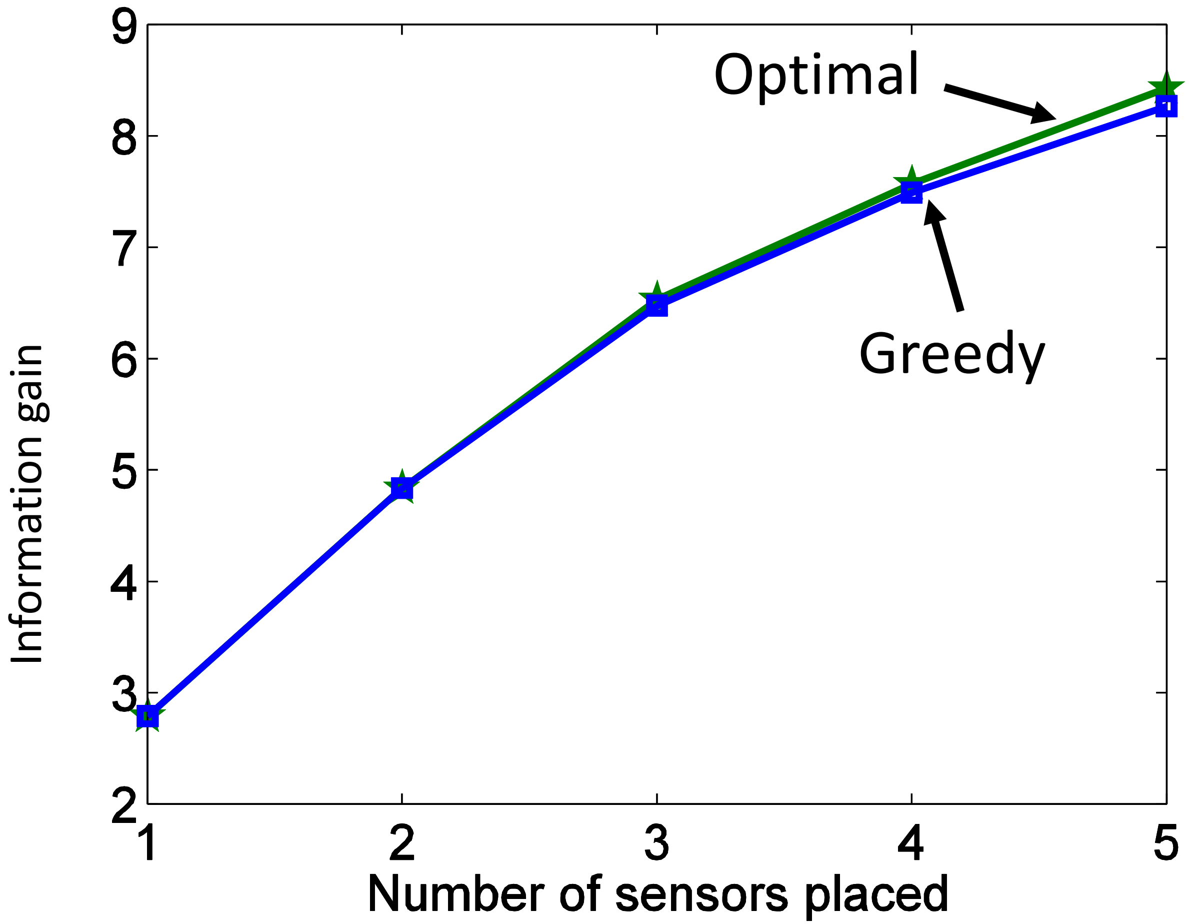
For i = 1 to k

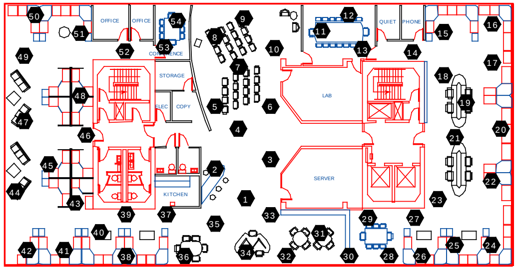
$s^* \leftarrow \arg\max_s F(\mathcal{A} \cup \{s\})$

$\mathcal{A} \leftarrow \mathcal{A} \cup \{s^*\}$

How well can this simple heuristic do?

Performance of greedy





Temperature data from sensor network

Greedy empirically close to optimal. Why?

One reason submodularity is useful

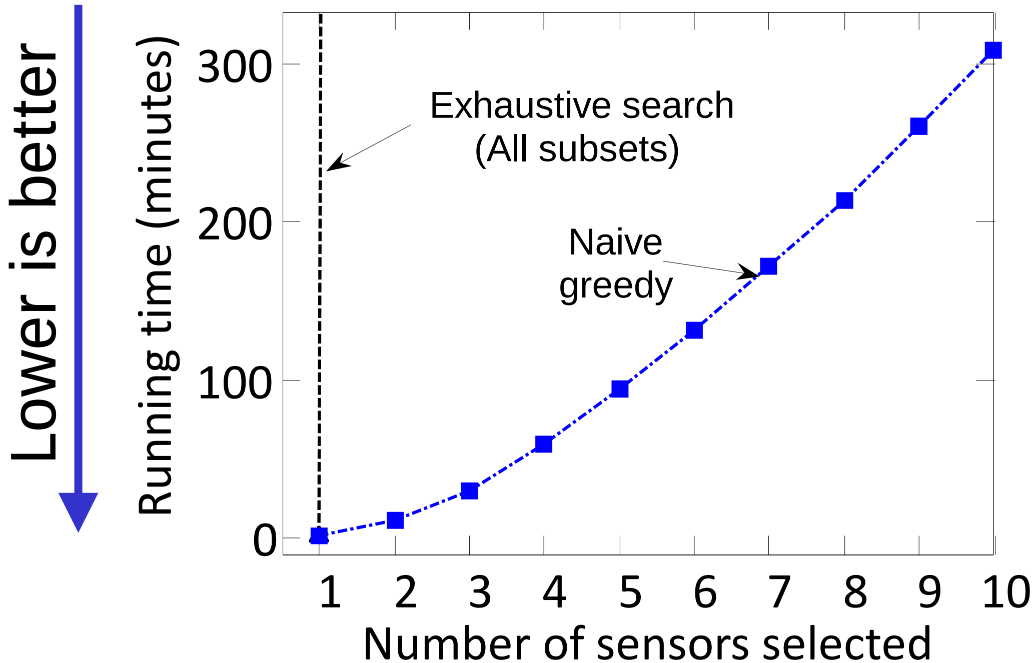
Theorem [Nemhauser, Fisher & Wolsey '78]

For monotonic submodular functions,
Greedy algorithm gives constant factor approximation

$$F(A_{greedy}) \geq \underbrace{(1-1/e)}_{\sim 63\%} F(A_{opt})$$

- Greedy algorithm gives near-optimal solution!
- In general, need to evaluate exponentially many sets to do better!
  [Nemhauser & Wolsey '78]
- Also many special cases are hard (set cover, mutual information, …)

Even greedy can be slow…



Sensor placement

Placing 10 sensors takes 5 hours on highly optimized implementation

Scaling up the greedy algorithm [Minoux ’78]

In round i+1,

- have picked $A_i = \{s_1,\ldots,s_i\}$
- pick $s_{i+1} = \text{argmax}_s\, F(A_i \cup \{s\})\text{-}F(A_i)$

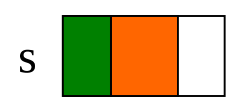
I.e., maximize “marginal benefit” $\otimes(s \mid A_i)$

$$\otimes(s \mid A_i) = F(A_i \cup \{s\})\text{-}F(A_i)$$

Key observation: Submodularity implies

$$i \leq j \;\; \Rightarrow \;\; \otimes(s \mid A_i) \;\geq\; \otimes(s \mid A_j)$$

$\otimes(s \mid A_i) \geq \otimes(s \mid A_{i+1})$

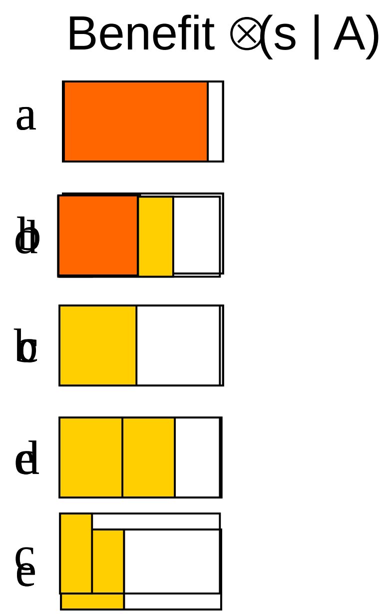


Marginal benefits can never increase!

"Lazy" greedy algorithm [Minoux '78]

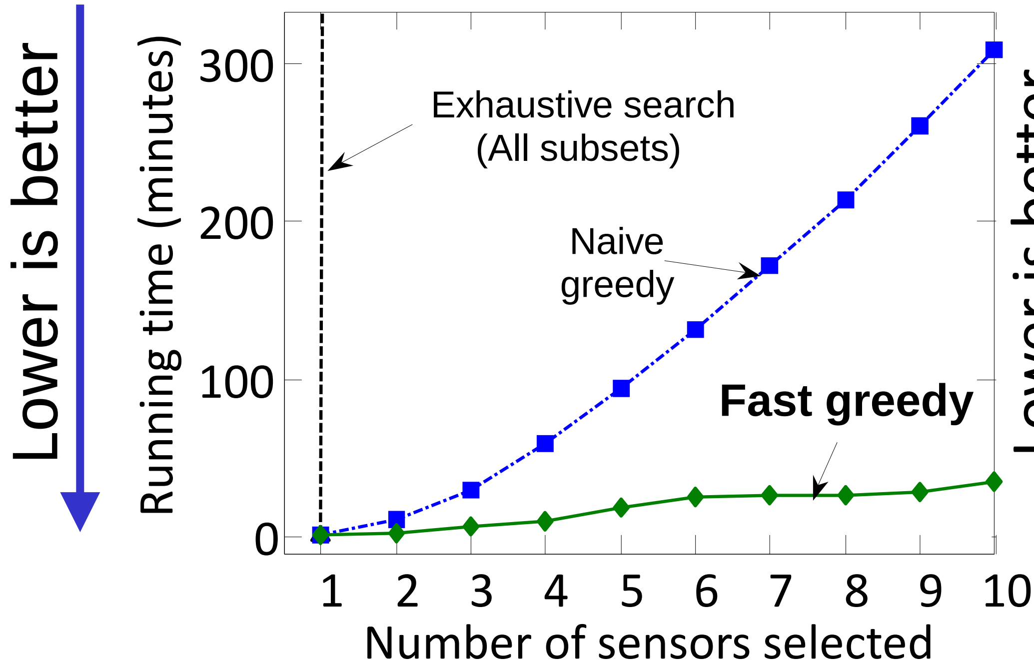
Lazy greedy algorithm:

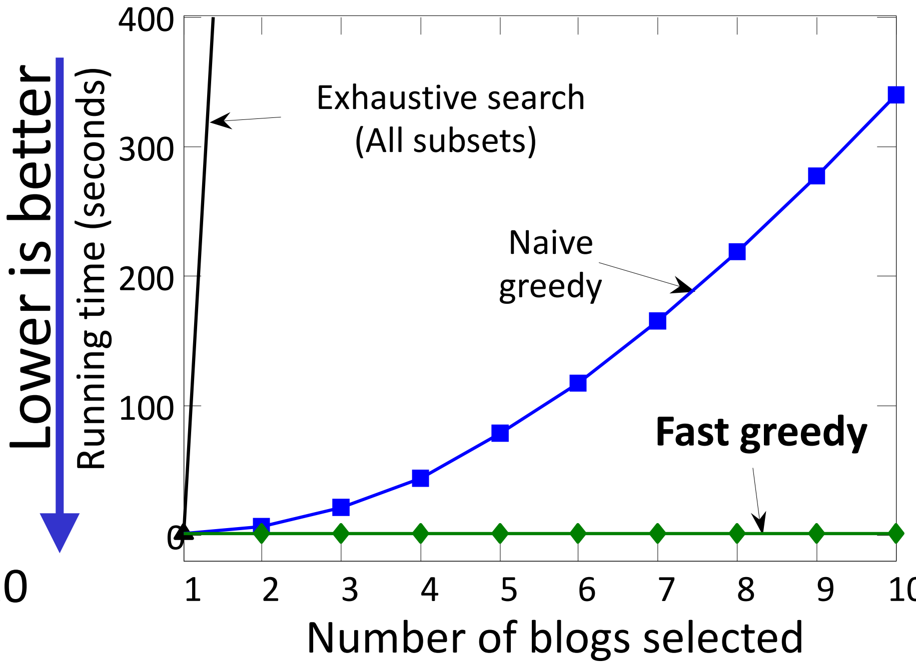
- First iteration as usual
- Keep an ordered list of marginal benefits $\otimes_i$ from previous iteration
- Re-evaluate $\otimes_i$ only for top element
- If $\otimes_i$ stays on top, use it, otherwise re-sort



Note: Very easy to compute online bounds, lazy evaluations, etc. [Leskovec, Krause et al. '07]

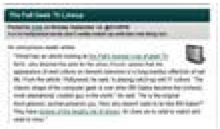
Empirical improvements [Leskovec, Krause et al'06]





Sensor placement

Blog selection

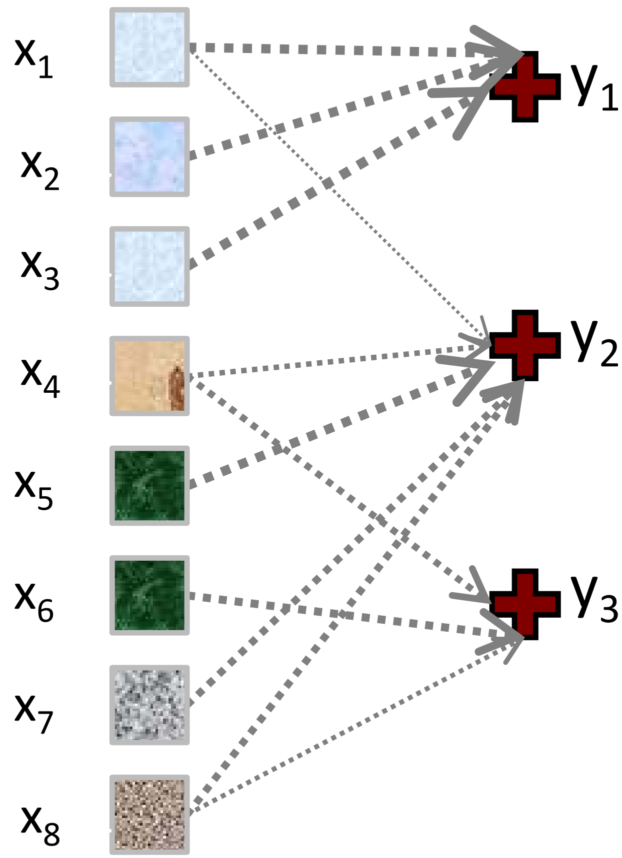


30x speedup

700x speedup

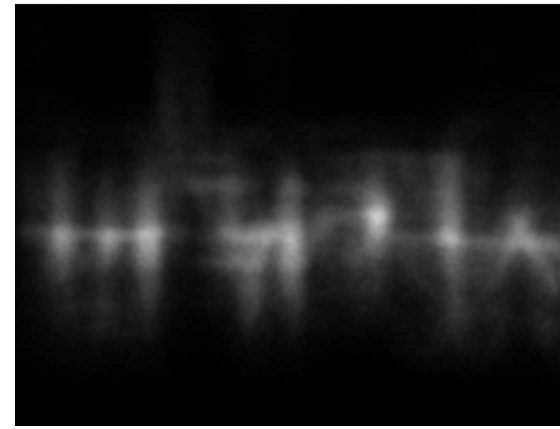
Multiple object detection [Barinova et al.'12]

x_j = index of hypothesis explaining x_j



Voting elements

Hypotheses

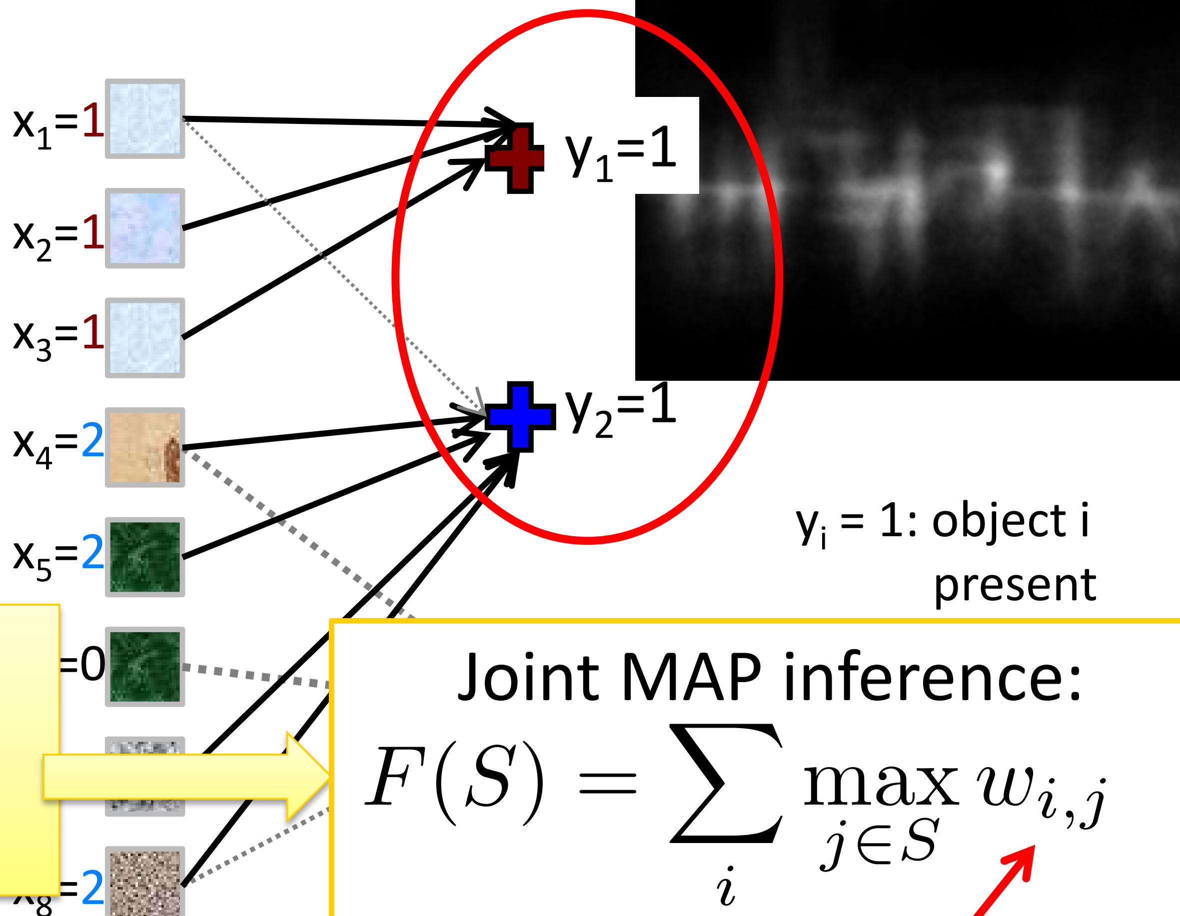


y_i = 1: object i present

y_i = 0: object i not present

Illustrations courtesy of Pushmeet Kohli

Multiple object detection [Barinova et al.'12]



x_j = index of hypothesis explaining x_j

y_i = 1: object i present

submodular maximization ☺

Voting elements

Joint MAP inference:

$$F(S) = \sum_i \max_{j \in S} w_{i,j}$$

Weight element i wrt hyp. j

Illustrations courtesy of Pushmeet Kohli

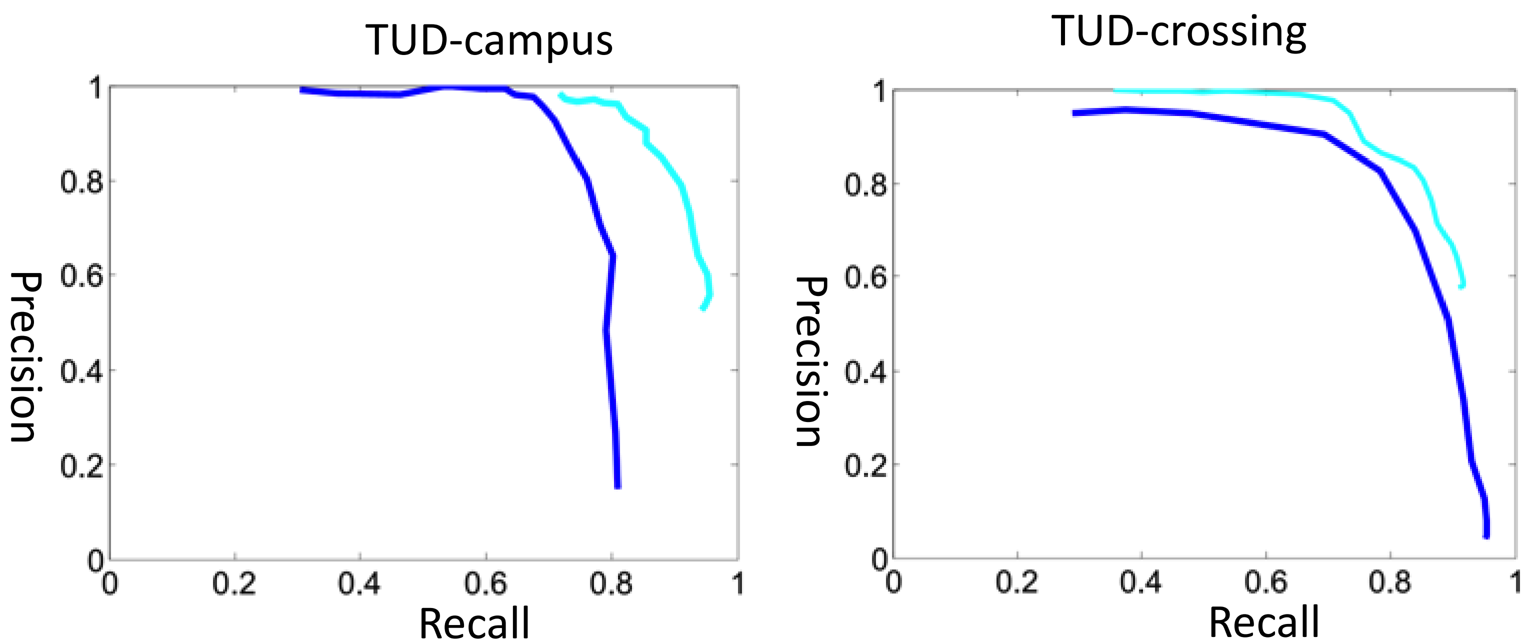
Inference

Datasets from [Andriluka et al. CVPR 2008]
(with strongly occluded pedestrians added)

Using the Hough forest trained in [Gall&Lempitsky CVPR09]

Illustrations courtesy of Pushmeet Kohli

Results for pedestrians detection

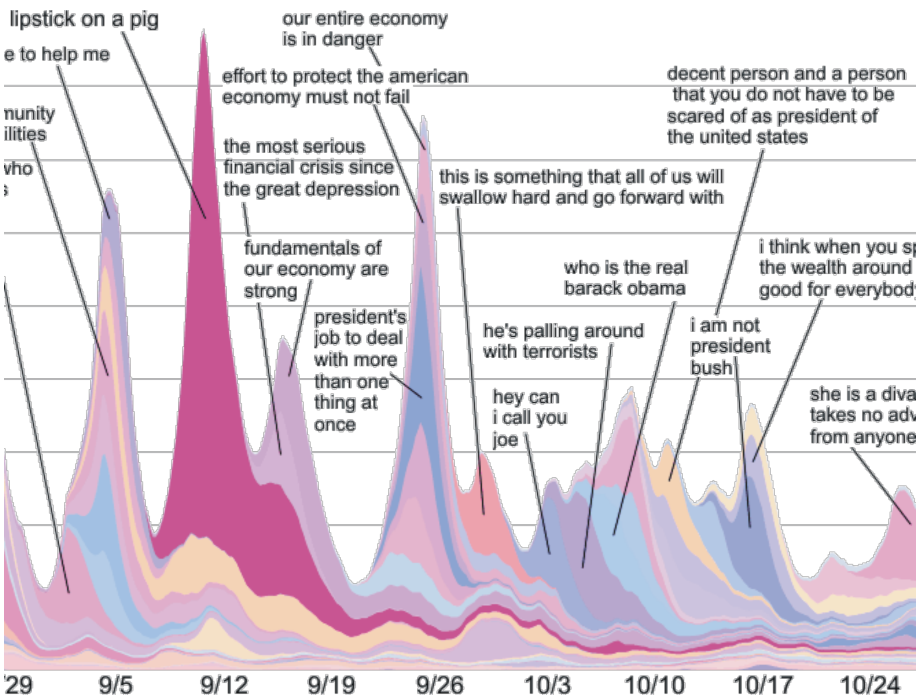


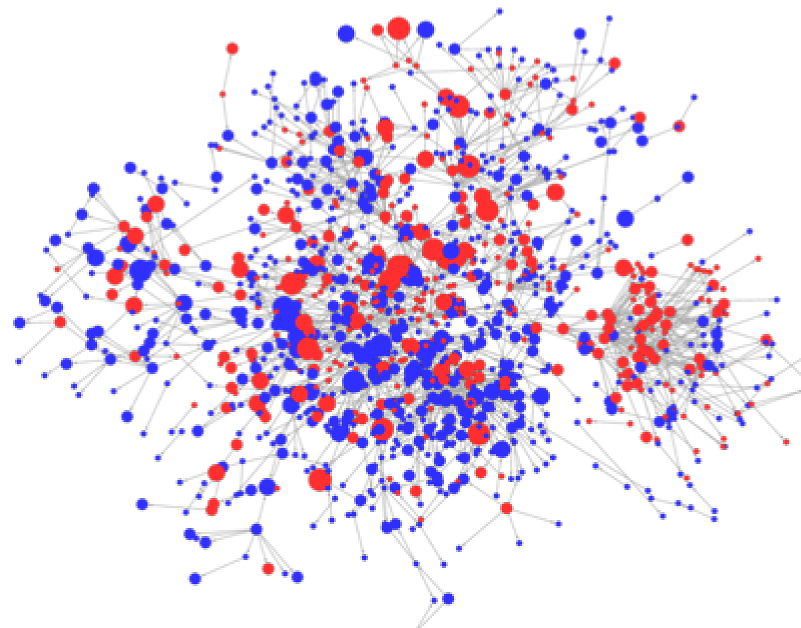
Blue = Hough transform + non-maximum suppression

Light-blue = greedy detection

submodularity for detection also in [Blaschko'11]

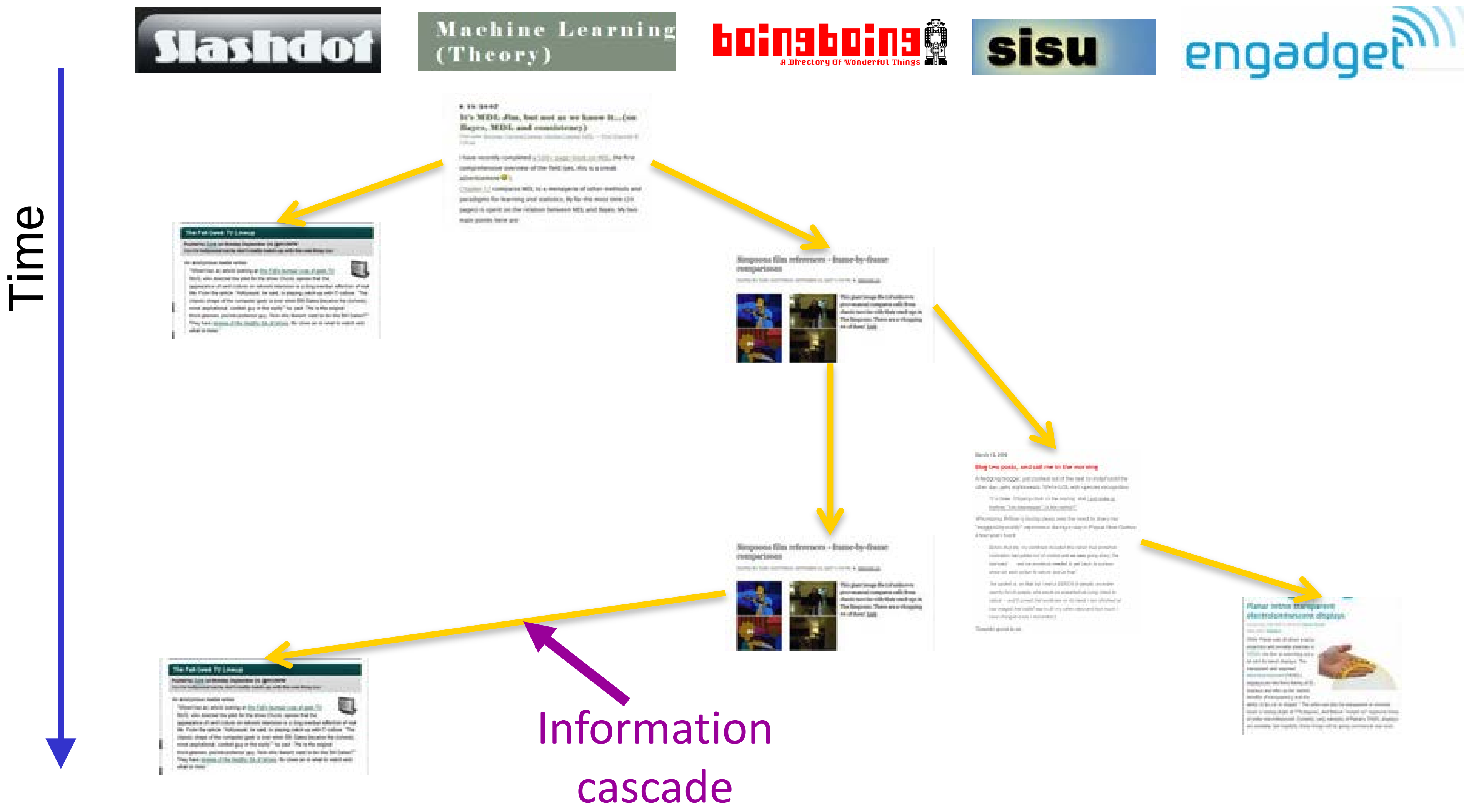
Network inference





How can we learn who influences whom?

Cascades in the Blogosphere



Inferring diffusion networks

[Gomez Rodriguez, Leskovec, Krause ACM TKDE 2012]

Given:

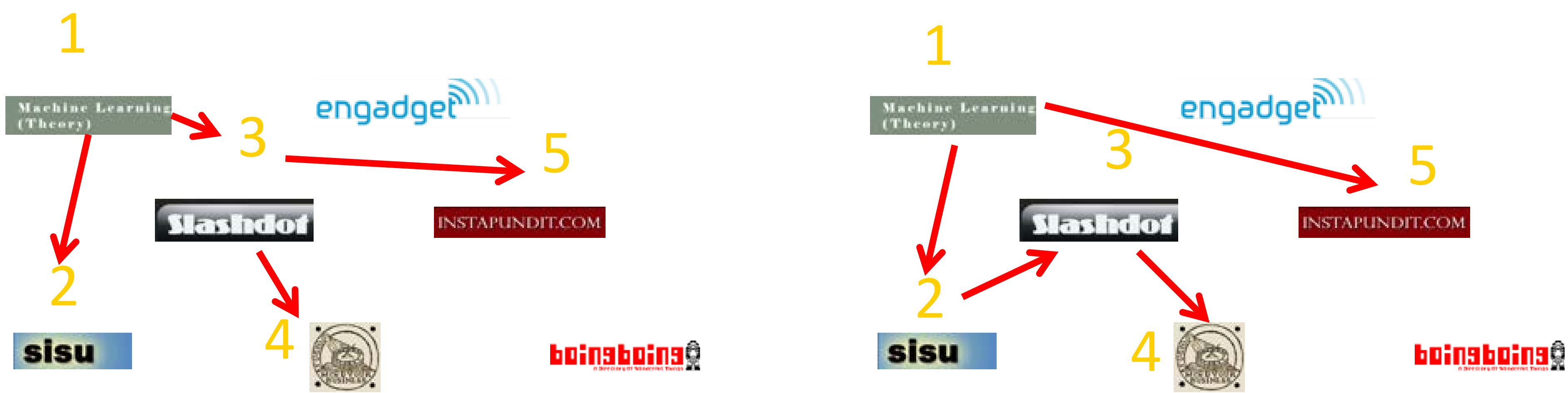
Want:

Given traces of influence, wish to infer sparse directed network G=(V,E)

➔ Formulate as optimization problem

$$E^* = \arg \max_{|E| \leq k} F(E)$$

Estimation problem

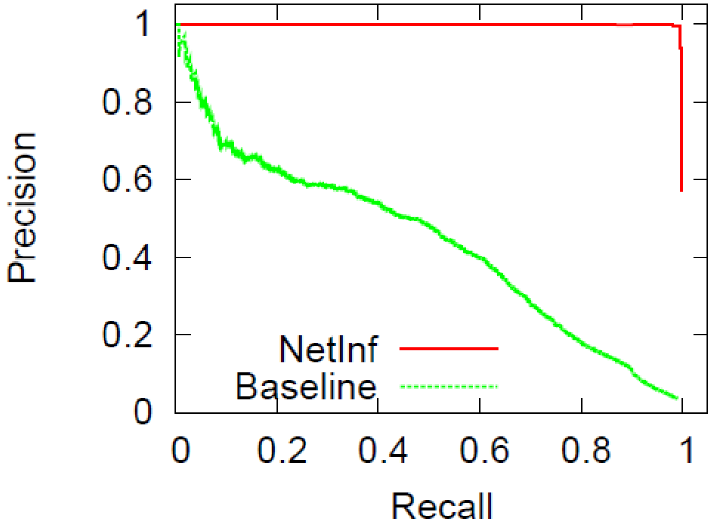


- Many influence trees T consistent with data
- For cascade C_i, model $P(C_i \mid T)$
- Find sparse graph that maximizes likelihood for all observed cascades

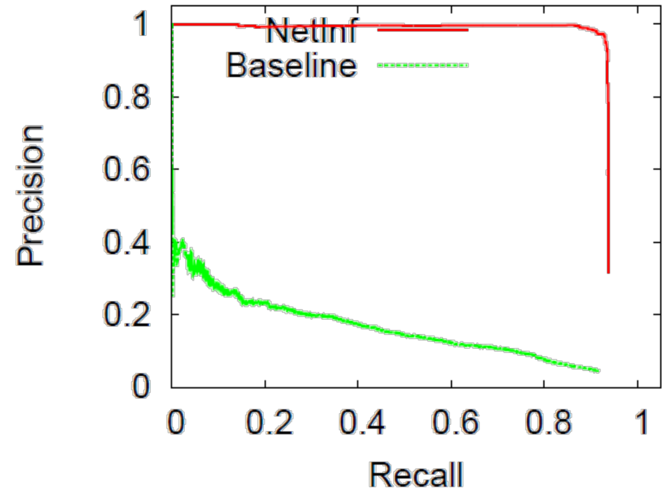
➔ Log likelihood monotonic submodular in selected edges

$$F(E) = \sum_i \log \max_{\text{tree } T \subseteq E} P(C_i \mid T)$$

Evaluation: Synthetic networks



1024 node hierarchical Kronecker exponential transmission model

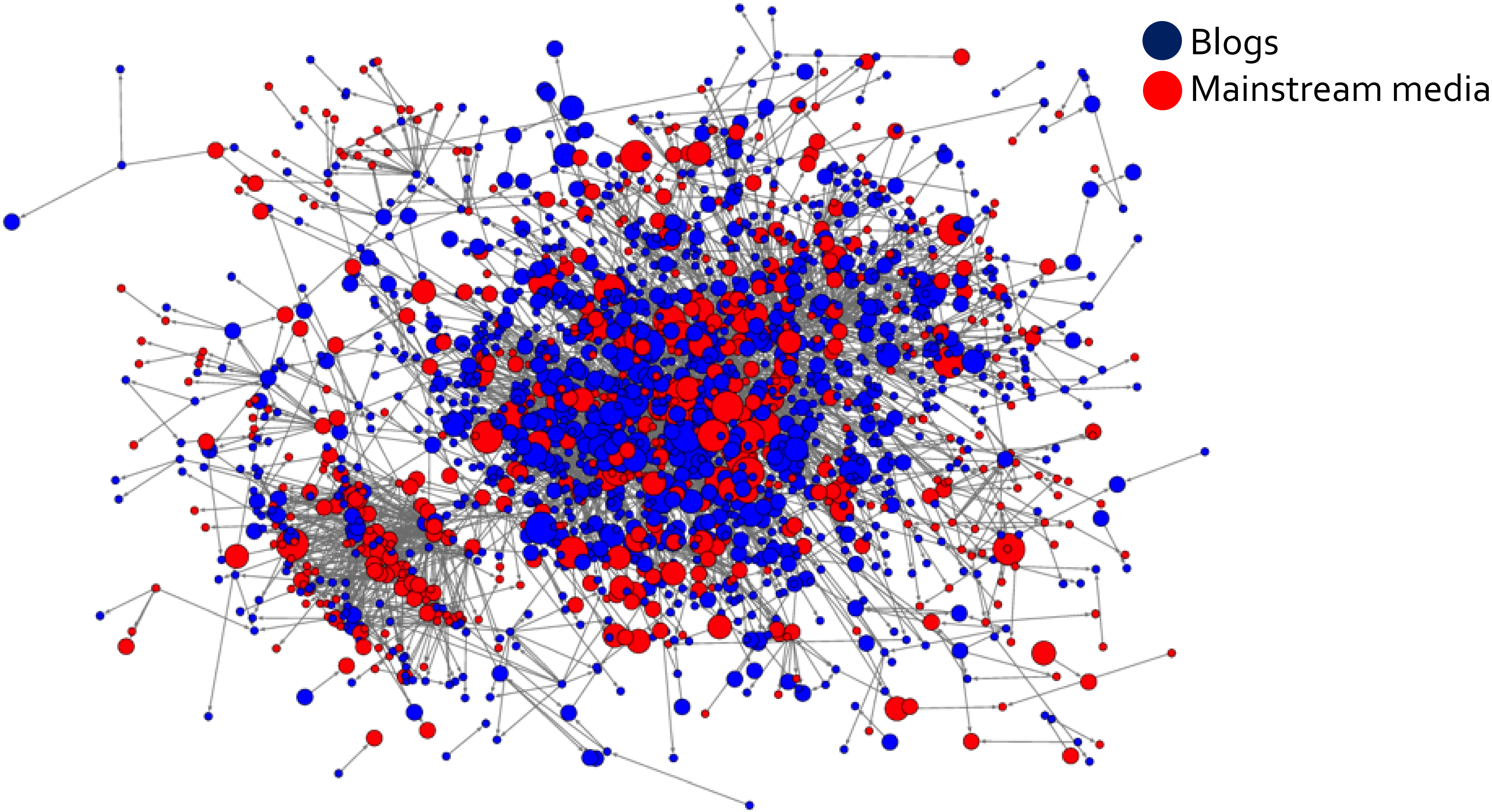


1000 node Forest Fire (α = 1.1) power law transmission model

- Performance does not depend on the network structure:
  - Synthetic Networks: Forest Fire, Kronecker, etc.
  - Transmission time distribution: Exponential, Power Law
- Break-even point of > 90%

Diffusion Network

[Gomez Rodriguez, Leskovec, Krause ACM TKDE 2012]

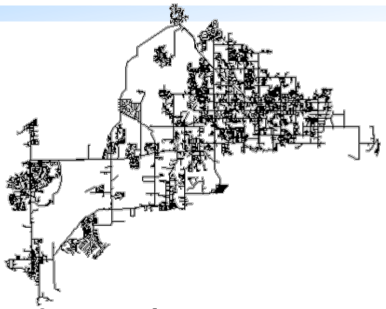


Actual network inferred from 172 million articles from 1 million news sources

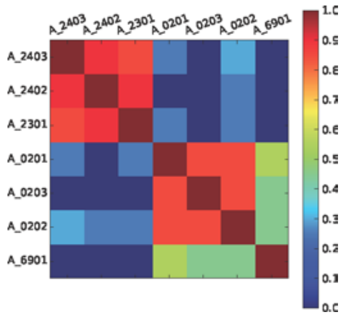
Submodular Sensing Problems

[with Guestrin, Leskovec, Singh, Sukhatme, …]

Environmental monitoring
[UAI'05, JAIR '08, ICRA '10]



Water distribution networks
[J WRPM '08]



Experiment design
[NIPS '10, '11, PNAS'13]

Machine Learning (Theory) Slashdot boingboing sisu engadget

Recommending blogs & news
[KDD '07, '10]

Can all be reduced to monotonic submodular maximization

Maximization: More complex constraints

- Approximate submodular maximization possible under a variety of constraints:
  - (Multiple) matroid constraints
  - Knapsack (non-constant cost functions)
  - Multiple matroid and knapsack constraints
  - Path constraints (Submodular orienteering)
  - Connectedness (Submodular Steiner)
  - Robustness (minimax)
  - ...

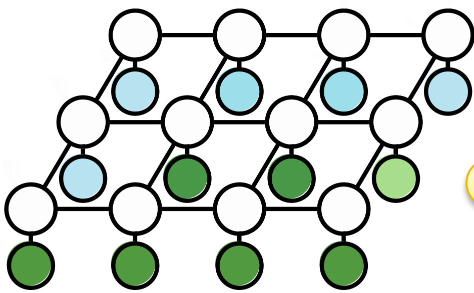
Greedy works well

Need **non-greedy** algorithms

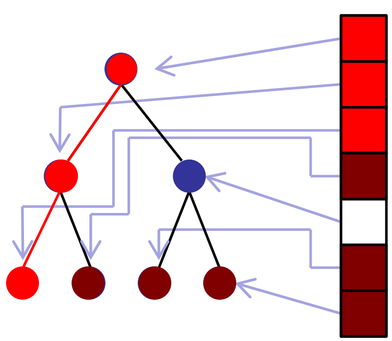
- Survey on „Submodular Function Maximization“ [Krause & Golovin ‘12] on submodularity.org

Two-faces of submodular functions

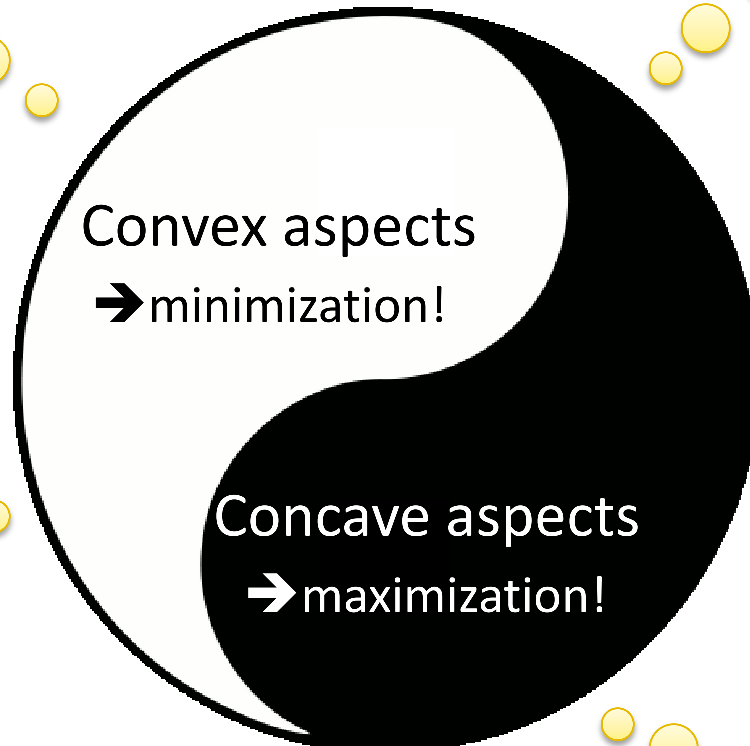
Cuts,
clustering,
similarity



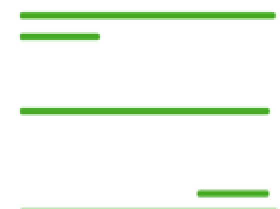
MAP inference



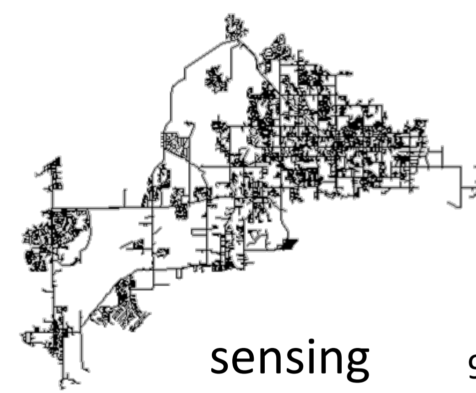
structured sparsity
regularization



Coverage,
diversity



summarization



sensing

	Maximization	**Minimization**
Unconstrained	NP-hard, but well-approximable (if nonnegative)	Polynomial time! Generally ineffcent (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 in general, still useful algorithms

Further topics in submodularity & ML

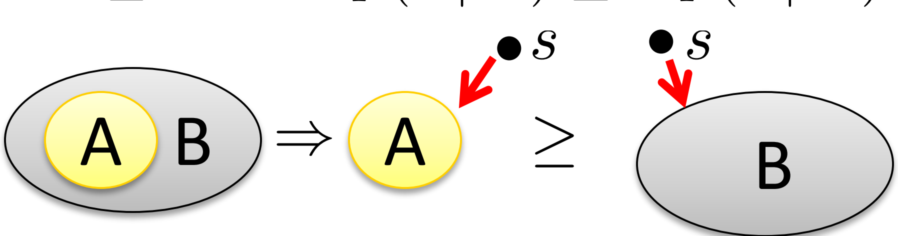
- Learning submodular functions
  - **Goal**: learn a submodular function from few samples
  - **Applications**: Preference elicitation, graph sketching, ...
  - Generally very hard
  - Possible under special structure (e.g., sparsity)
- Online submodular optimization
  - **Goal**: Repeatedly solve submodular optimization problems
  - **Applications**: Recommender systems
  - No regret algorithms for online submodular min & max
- Active learning with submodular functions
  - **Goal**: Adaptive select elements given feedback
  - **Applications**: Active learning, experimental design
  - *Adaptive submodularity* generalizes SFs to policies

From sets to policies

[Golovin & Krause JAIR 2011, IJCAI-JAIR Best Paper 2013]

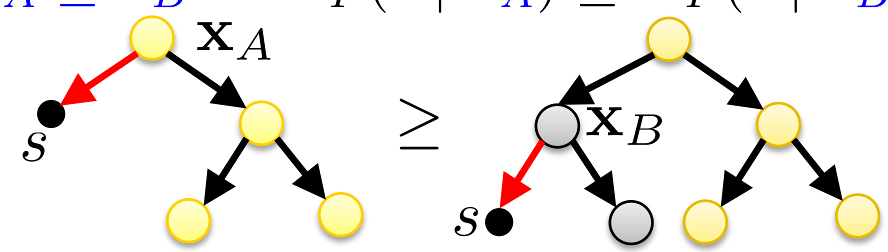
Submodularity	⇨ **Adaptive submodularity**
Applies to: set functions	policies, value functions

$$A \subseteq B \Rightarrow \Delta_F(s \mid A) \geq \Delta_F(s \mid B)$$



$$\max_A F(A)$$

$$\mathbf{x}_A \preceq \mathbf{x}_B \Rightarrow \Delta_F(s \mid \mathbf{x}_A) \geq \Delta_F(s \mid \mathbf{x}_B)$$



$$\max_\pi F(\pi)$$

Greedy algorithm provides

- *(1-1/e)* for max. w card. const.
- *1/(p+1)* for p-indep. systems
- *log Q* for min-cost-cover
- *4* for min-sum-cover

Greedy policy provides

- *(1-1/e)* for max. w card. const.
- *1/(p+1)* for p-indep. systems
- *log Q* for min-cost-cover
- *4* for min-sum-cover

Other directions

- Game theory
  - Equilibria in cooperative (supermodular) games / fair allocations
  - Price of anarchy in non-cooperative games
  - Incentive compatible submodular optimization
- Generalizations of submodular functions
  - L#-convex / discrete convex analysis
  - XOS/Subadditive functions
- More optimization algorithms
  - Robust submodular maximization
  - Maximization and minimization under complex constraints
  - Multilinear extension and applications
  - Submodular-supermodular procedure / semigradient methods

Further resources

- submodularity.org
  - Tutorial Slides
  - Annotated bibliography
  - Matlab Toolbox for Submodular Optimization
  - Links to workshops and related meetings
- discml.cc
  - NIPS Workshops on Discrete Optimization in Machine Learning
  - Videos of invited talks on videolectures.net

…

Conclusions

- Discrete optimization abundant in applications
- Fortunately, some of those have structure: submodularity
- Submodularity can be exploited to develop efficient, scalable algorithms with strong guarantees
- Many exciting research directions! ☺