

10-418 / 10-618 Machine Learning for Structured Data



Machine Learning Department School of Computer Science Carnegie Mellon University

Structured SVM

Matt Gormley Lecture 15 Oct. 16, 2019

Reminders

- Midterm Exam
 - Thu, Oct. 17 at 6:30pm 8:00pm
- Homework 3: Structured SVM
 - Out: Fri, Oct. 18
 - Due: Fri, Nov. 1 at 11:59pm

aka. Max-Margin Markov Networks (M³Ns)

STRUCTURED SVM

Structured SVM

Whiteboard

- Warmup: Binary SVM
- Warmup: Binary SVM Hinge Loss
- Structured Large Margin
- Structured Hinge Loss
- Gradient of Structured Hinge Loss
- SGD for Structured SVM
- Loss Augmented MAP Inference

Max vs "Soft-Max" Margin



SVMs:

$$\min_{\mathbf{w}} k ||\mathbf{w}||^2 - \sum_{i} \left(\mathbf{w}^{\top} \mathbf{f}_i(\mathbf{y}^i) - \max_{\mathbf{y}} \left(\mathbf{w}^{\top} \mathbf{f}_i(\mathbf{y}) + \ell_i(\mathbf{y}) \right) \right)$$

Hard (Penalized) Margin

Maxent:

$$\min_{\mathbf{w}} \ k||w||^2 - \sum_i \left(\mathbf{w}^\top \mathbf{f}_i(\mathbf{y}^i) - \log \sum_{\mathbf{y}} \exp \left(\mathbf{w}^\top \mathbf{f}_i(\mathbf{y}) \right) \right)$$
Soft Margin

- Very similar! Both try to make the true score better than a function of the other scores.
 - The SVM tries to beat the augmented runner-up
 - The maxent classifier tries to beat the "soft-max"

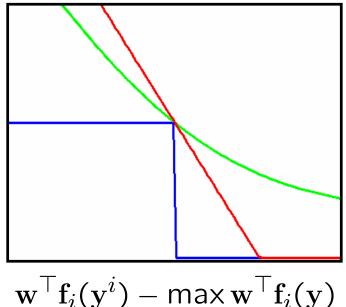
Hinge Loss



Consider the per-instance SVM objective:

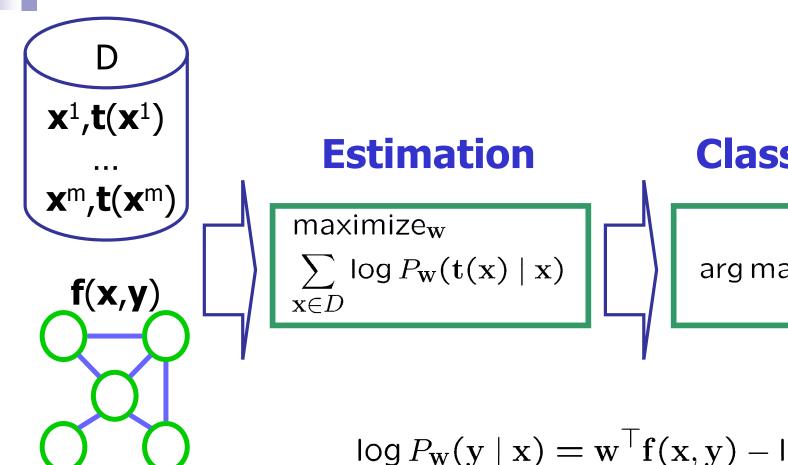
$$\min_{\mathbf{w}} k ||\mathbf{w}||^2 - \sum_{i} \left(\mathbf{w}^{\top} \mathbf{f}_i(\mathbf{y}^i) - \max_{\mathbf{y}} \left[\mathbf{w}^{\top} \mathbf{f}_i(\mathbf{y}) + \ell_i(y) \right] \right)$$

- This is called the "hinge loss"
 - Upper bounds zero-one loss
 - Unlike maxent / log loss, you stop gaining objective once the true label wins by enough
 - You can start from here and derive the SVM objective



$$\mathbf{w}^{\top}\mathbf{f}_{i}(\mathbf{y}^{i}) - \max_{\mathbf{y} \neq \mathbf{y}^{i}} \mathbf{w}^{\top}\mathbf{f}_{i}(\mathbf{y})$$

Max (Conditional) Likelihood



Classification

 $arg max_y w^T f(x, y)$

$$\log P_{\mathbf{w}}(\mathbf{y} \mid \mathbf{x}) = \mathbf{w}^{\top} \mathbf{f}(\mathbf{x}, \mathbf{y}) - \log Z_{\mathbf{w}}(\mathbf{x})$$

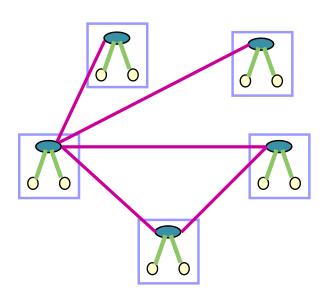
Don't need to learn entire distribution!

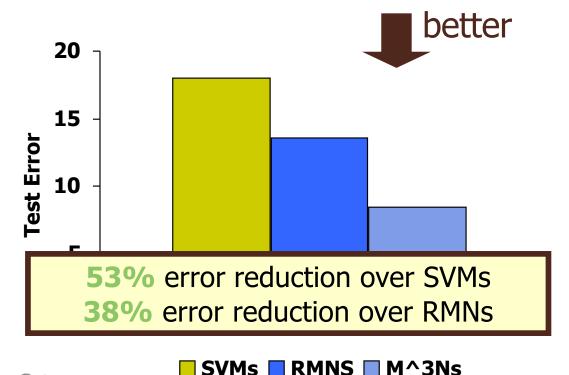
Results: Handwriting Recognition

quadratic cubic raw ror (average per-character) Length: ~8 chars 30 pixels kernel kernel Letter: 16x8 pixels 10-fold Train/Test 25 . better 5000/50000 letters 20 600/6000 words 15 Models: Multiclass-SVMs* **CRFs** 45% error reduction over linear CRFs M³ nets 33% error reduction over multiclass SVMs 0 + MC-SVMs **CRFs** M³ nets

Results: Hypertext Classification

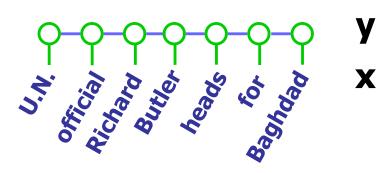
- WebKB dataset
 - Four CS department websites: 1300 pages/3500 links
 - Classify each page: faculty, course, student, project, other
 - Train on three universities/test on fourth
- Inference: loopy belief propagation
- Learning: relaxed dual





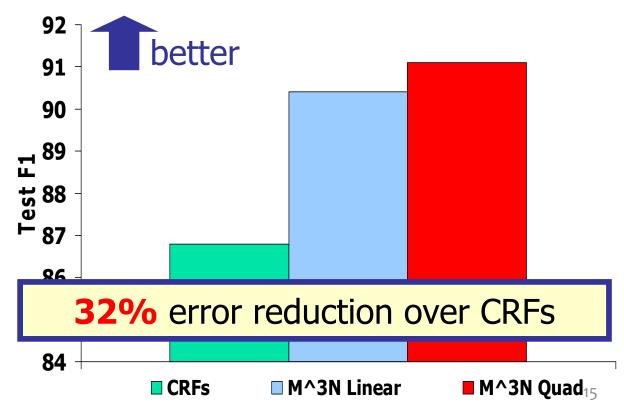
Named Entity Recognition

- Locate and classify named entities in sentences:
 - 4 categories: organization, person, location, misc.
 - e.g. "U.N. official Richard Butler heads for Baghdad".
- CoNLL 03 data set (200K words train, 50K words test)

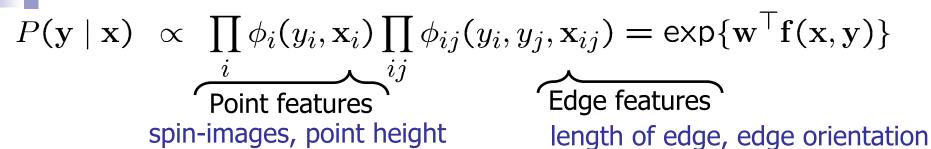


 $y_i = org/per/loc/misc/none$

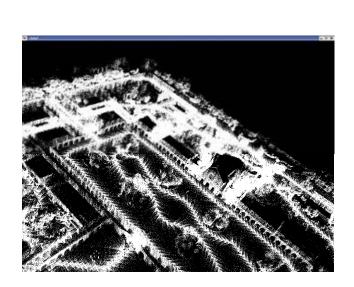
$$f(y_i, x) = [..., I(y_i = \text{org}, x_i = \text{``U.N.''}), I(y_i = \text{per}, x_i = \text{capitalized}), I(y_i = \text{loc}, x_i = \text{known city}), ...,]$$

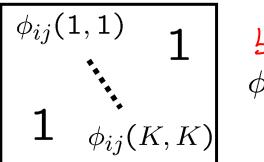


Associative Markov networks

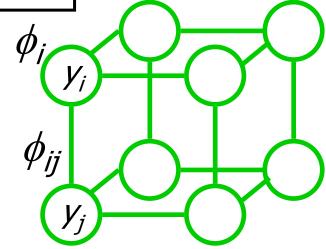


"associative" $\phi_{ij}(y_i, y_j) =$

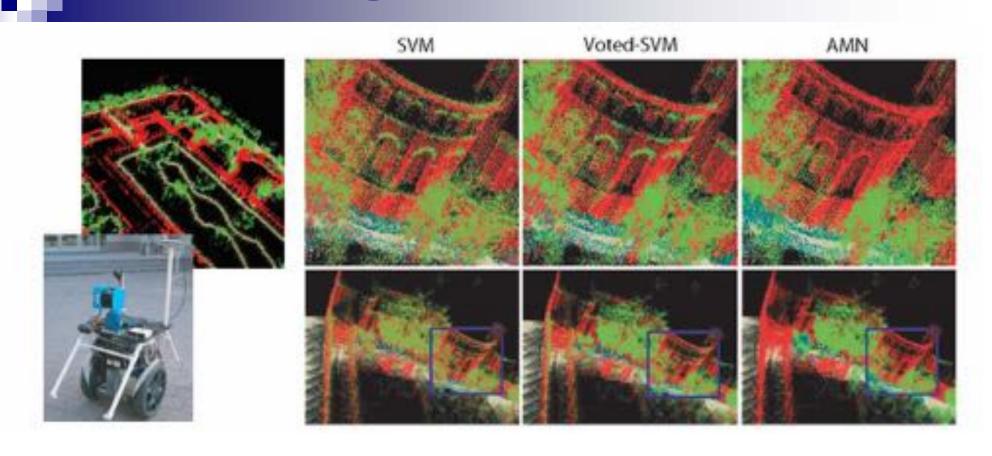








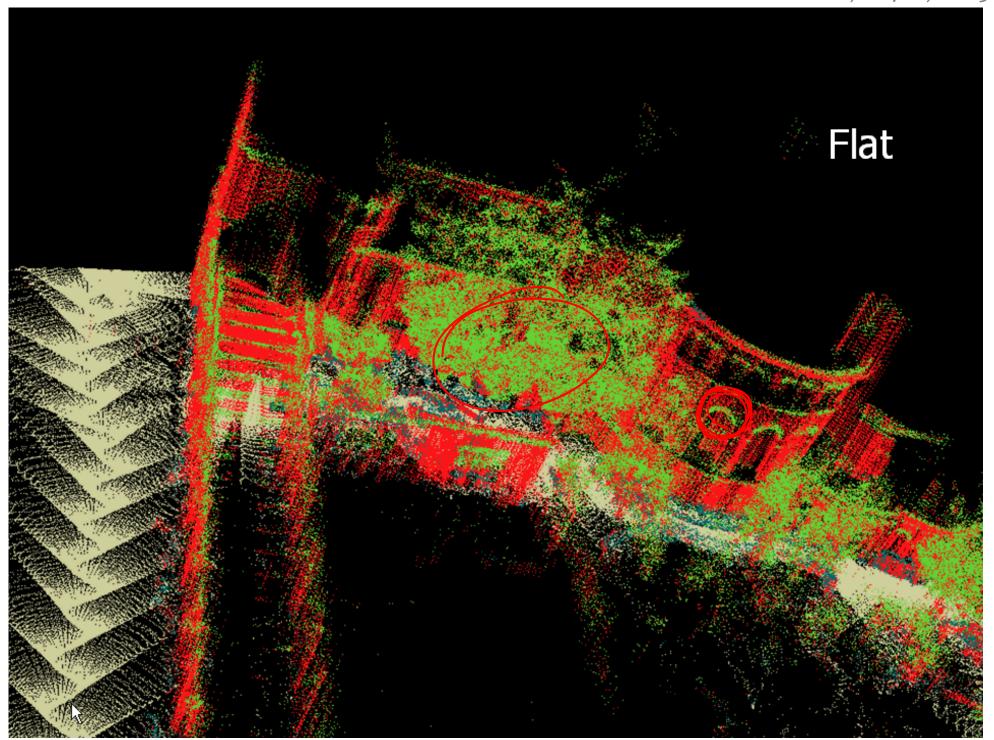
Max-margin AMNs results



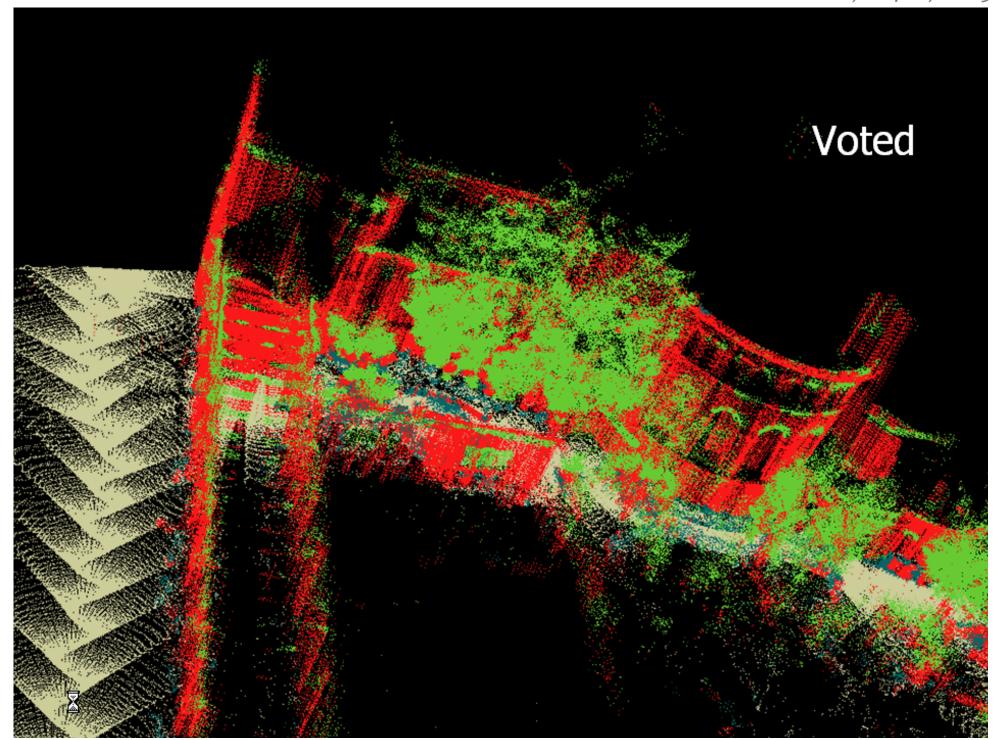
Label: ground, building, tree, shrub

Training: 30 thousand points Testing: 3 million points

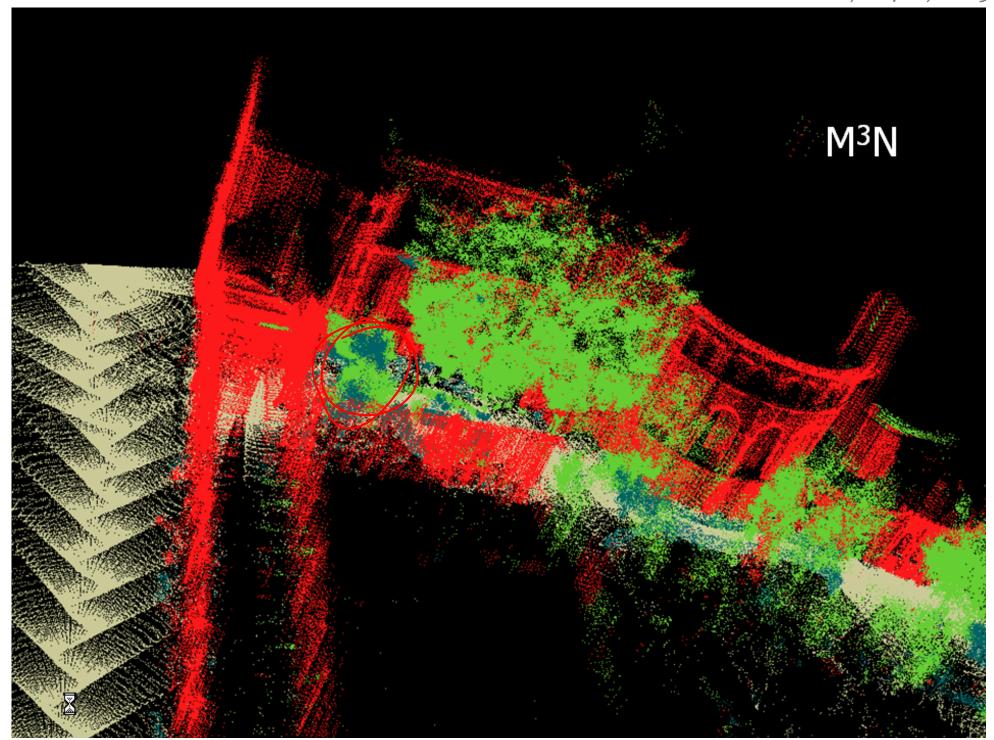
Slide from Guestrin, 10-701, 2005



Slide from Guestrin, 10-701, 2005



Slide from Guestrin, 10-701, 2005



Segmentation results

Hand labeled 180K test points

Model	Accuracy
SVM	68%
V-SVM	73%
M ³ N	93%

