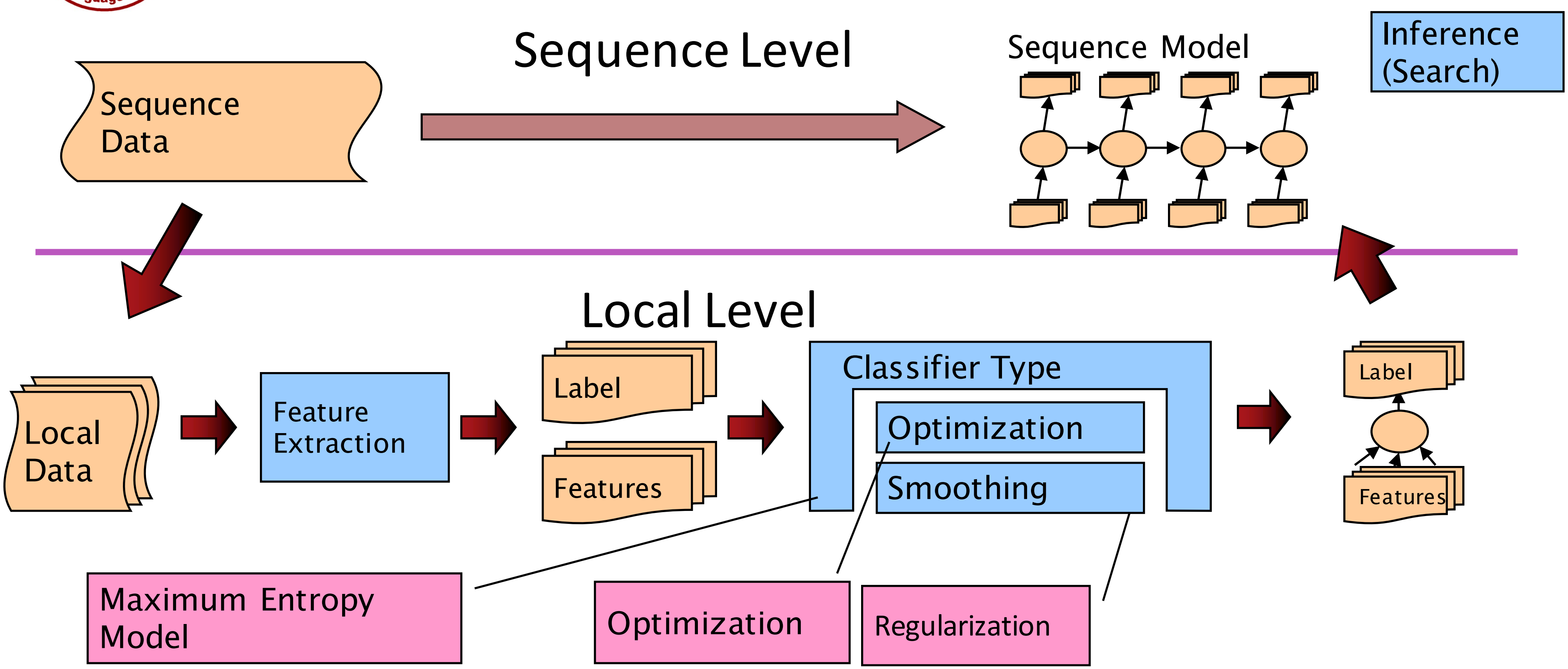
Maxent Models & Deep Learning

1. Last bits of maxent (sequence) models
   1. MEMMs vs. CRFs
   2. Smoothing/regularization in maxent models
2. Deep Learning
   1. What is it? Why is it good? (Part 1)
   2. From logistic regression to neural networks
   3. Word vector representations

Maximum entropy sequence models

Maximum entropy Markov models (MEMMs) a.k.a. Conditional Markov models

Inference in Systems



CRFs [Lafferty, Pereira, and McCallum 2001]

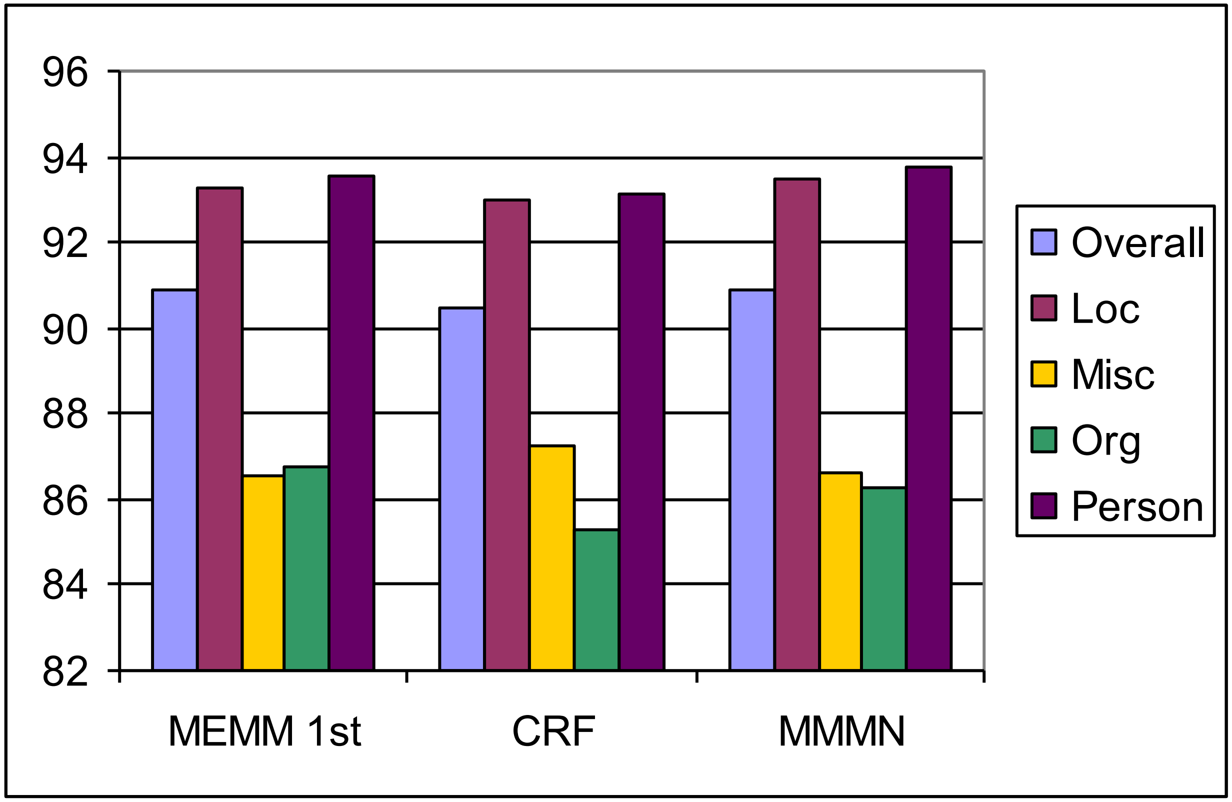
- Another sequence model: Conditional Random Fields (CRFs)
- A whole-sequence conditional model rather than a chaining of local models.

$$P(c \mid d, \lambda) = \frac{\exp \sum_i \lambda_i f_i(c, d)}{\sum_{c'} \exp \sum_i \lambda_i f_i(c', d)}$$

- The space of c's is now the space of sequences
  - But if the features f_i remain local, the conditional sequence likelihood can be calculated exactly using dynamic programming
- Training is slower, but CRFs avoid causal-competition biases
- These (or a variant using a max margin criterion) are seen as the state-of-the-art these days … but in practice they usually work much the same as MEMMs.

Christopher Manning

CoNLL 2003 NER shared task
Results on English Devset



Smoothing/Priors/ Regularization for Maxent Models

Smoothing: Issues of Scale

- Lots of features:
  - NLP maxent models can have ten million features.
  - Even storing a single array of parameter values can have a substantial memory cost.
- Lots of sparsity:
  - Overfitting very easy – we need smoothing!
  - Many features seen in training will never occur again at test time.
- Optimization problems:
  - Feature weights can be infinite, and iterative solvers can take a long time to get to those infinities.

Smoothing: Issues

- Assume the following empirical distribution:

Heads	Tails
h	t

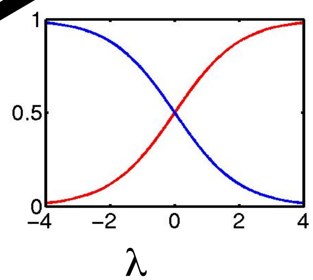
- Features: {Heads}, {Tails}
- We'll have the following softmax model distribution:

$$p_{\text{HEADS}} = \frac{e^{\lambda_H}}{e^{\lambda_H} + e^{\lambda_T}} \qquad p_{\text{TAILS}} = \frac{e^{\lambda_T}}{e^{\lambda_H} + e^{\lambda_T}}$$

- Really, only one degree of freedom ($\lambda = \lambda_H - \lambda_T$)

$$p_{\text{HEADS}} = \frac{e^{\lambda_H} e^{-\lambda_T}}{e^{\lambda_H} e^{-\lambda_T} + e^{\lambda_T} e^{-\lambda_T}} = \frac{e^{\lambda}}{e^{\lambda} + e^{0}} = \frac{e^{\lambda}}{e^{\lambda} + 1} \qquad p_{\text{TAILS}} = \frac{e^{0}}{e^{\lambda} + e^{0}} = \frac{1}{1 + e^{\lambda}}$$

Logistic regression!

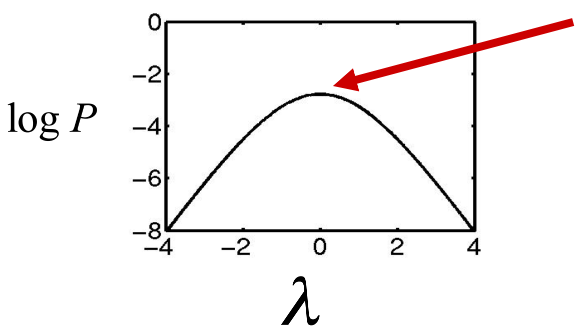


Smoothing: Issues

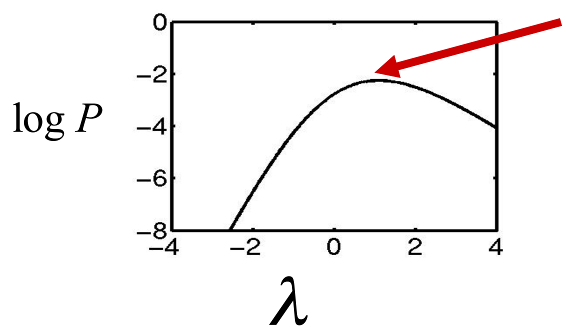
- The data likelihood in this model is:

$$\log P(h,t \mid \lambda) = h \log p_{\text{HEADS}} + t \log p_{\text{TAILS}}$$

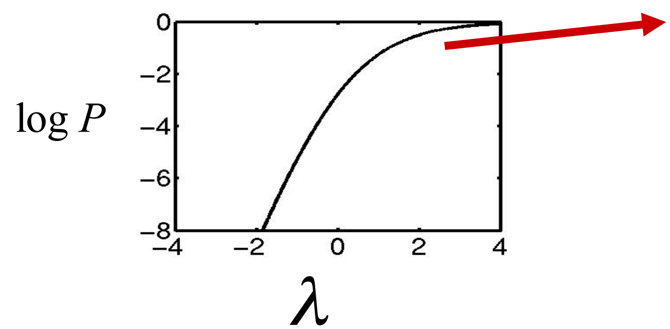
$$\log P(h,t \mid \lambda) = h\lambda - (t+h)\log(1+e^{\lambda})$$



Heads	Tails
2	2



Heads	Tails
3	1

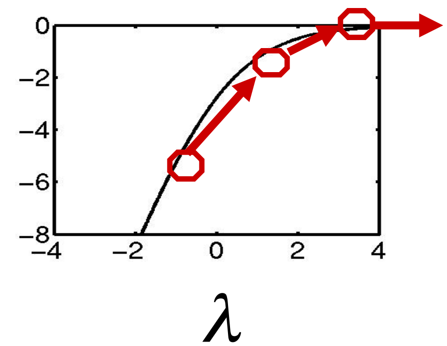


Heads	Tails
4	0

Smoothing: Early Stopping

- In the 4/0 case, there were two problems:
  - The optimal value of λ was ∞, which is a long trip for an optimization procedure
  - The learned distribution is just as spiked as the empirical one – no smoothing

- One way to solve both issues is to just stop the optimization early, after a few iterations:
  - The value of λ will be finite (but presumably big)
  - The optimization won't take forever (clearly)
  - Commonly used in early maxent work
    - Has seen a revival in deep learning ☺



Heads	Tails
4	0

Input

Heads	Tails
1	0

Output

Smoothing: Priors (MAP)

- What if we had a prior expectation that parameter values wouldn't be very large?
- We could then balance evidence suggesting large parameters (or infinite) against our prior.
- The evidence would never totally defeat the prior, and parameters would be smoothed (and kept finite!).
- We can do this explicitly by changing the optimization objective to maximum posterior likelihood:

$$\log P(C,\lambda \mid D) = \log P(\lambda) + \log P(C \mid D,\lambda)$$

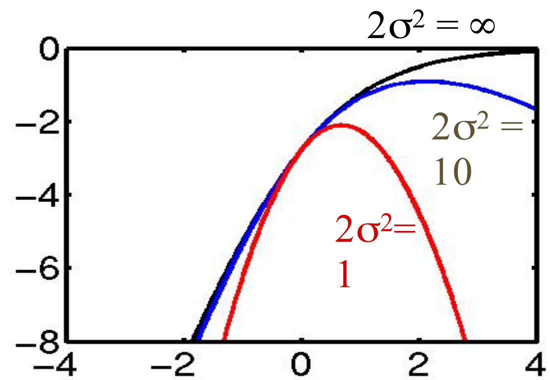
Posterior Prior Evidence

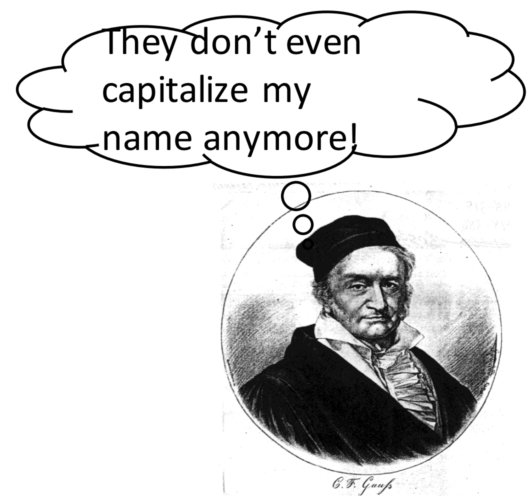
Smoothing: Priors

- Gaussian, or quadratic, or L_2 priors:
  - Intuition: parameters shouldn't be large.
  - Formalization: prior expectation that each parameter will be distributed according to a gaussian with mean μ and variance σ^2.

$$P(\lambda_i) = \frac{1}{\sigma_i \sqrt{2\pi}} \exp\left(- \frac{(\lambda_i - \mu_i)^2}{2\sigma_i^2} \right)$$

  - Penalizes parameters for drifting too far from their mean prior value (usually μ=0).
  - $2\sigma^2$=1 works surprisingly well.



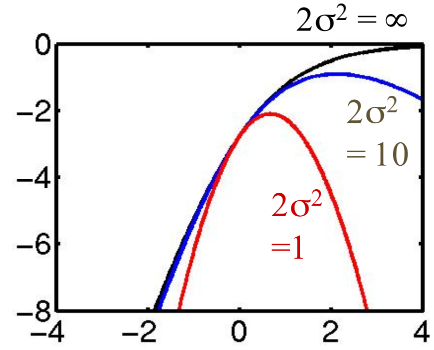


Smoothing: Priors

- If we use gaussian priors / L_2 regularization:
  - Trade off some expectation-matching for smaller parameters.
  - When multiple features can be recruited to explain a data point, the more common ones generally receive more weight.
  - Accuracy generally goes up!
- Change the objective:

$$\log P(C,\lambda \mid D) = \log P(C \mid D,\lambda) + \log P(\lambda)$$

$$\log P(C,\lambda \mid D) = \sum_{(c,d)\in(C,D)} P(c \mid d,\lambda) - \sum_i \frac{(\lambda_i - \mu_i)^2}{2\sigma_i^2} + k$$



- Change the derivative:

$$\partial \log P(C,\lambda \mid D) / \partial \lambda_i = \mathrm{actual}(f_i, C) - \mathrm{predicted}(f_i, \lambda) - (\lambda_i - \mu_i)/\sigma^2$$

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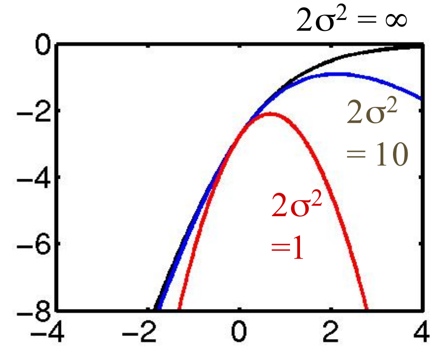
- Change the derivative:

$$\partial \log P(C,\lambda \mid D) / \partial \lambda_i = \text{actual}(f_i, C) - \text{predicted}(f_i, \lambda) - \lambda_i / \sigma^2$$



Taking prior mean as 0

Example: NER Smoothing

Because of smoothing, the more common prefix and single-tag features have larger weights even though entire-word and tag-pair features are more specific.

Local Context

	Prev	Cur	Next
State	Other	???	???
Word	at	Grace	Road
Tag	IN	NNP	NNP
Sig	x	Xx	Xx

Feature Weights

Feature Type	Feature	PERS	LOC
Previous word	*at*	-0.73	0.94
Current word	*Grace*	0.03	0.00
Beginning bigram	*<G*	0.45	-0.04
Current POS tag	NNP	0.47	0.45
Prev and cur tags	IN NNP	-0.10	0.14
Previous state	Other	-0.70	-0.92
Current signature	Xx	0.80	0.46
Prev state, cur sig	O-Xx	0.68	0.37
Prev-cur-next sig	x-Xx-Xx	-0.69	0.37
P. state - p-cur sig	O-x-Xx	-0.20	0.82
…			
Total:		**-0.58**	**2.68**

Example: Named Entity Feature Overlap

Grace is correlated with PERSON, but does not add much evidence on top of already knowing prefix features.

Local Context

	Prev	Cur	Next
State	Other	???	???
Word	at	Grace	Road
Tag	IN	NNP	NNP
Sig	x	Xx	Xx

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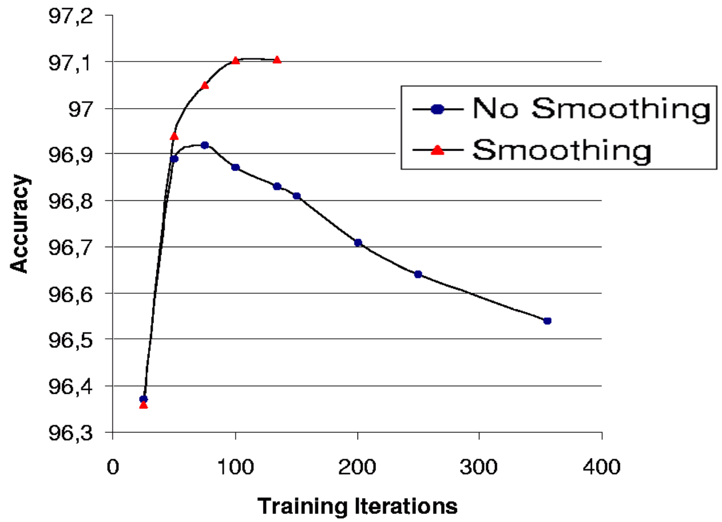
…			
Total:		**-0.58**	**2.68**

Example: POS Tagging

- From (Toutanova et al., 2003):

	Overall Accuracy	Unknown Word Acc
Without Smoothing	96.54	85.20
With Smoothing	97.10	88.20

DevTest Performance



- Smoothing helps:
  - Softens distributions.
  - Pushes weight onto more explanatory features.
  - Allows many features to be dumped safely into the mix.
  - Speeds up convergence (if both are allowed to converge)!

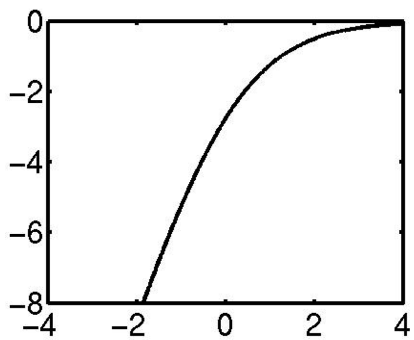
Christopher Manning

Smoothing / Regularization

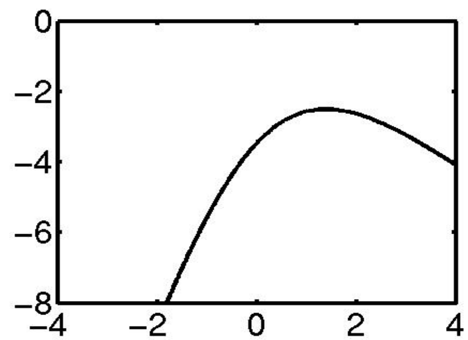
- Talking of "priors" and "MAP estimation" is Bayesian language
- In frequentist statistics, people will instead talk about using "regularization", and in particular, a gaussian prior is "L_2 regularization"
- The choice of names makes no difference to the math
- Recently, L_1 regularization is also very popular
  - Gives sparse solutions – most parameters become zero [Yay!]
  - Harder optimization problem (non-continuous derivative)

Smoothing: Virtual Data

- Another option: smooth the data, not the parameters.
- Example:



Heads	Tails
4	0



Heads	Tails
5	1

  - Equivalent to adding two extra data points.
  - Similar to add-one smoothing for generative models.
- For feature-based models, hard to know what artificial data to create!

Smoothing: Count Cutoffs

- In NLP, features with low empirical counts are often dropped.
  - Very weak and indirect smoothing method.
  - Equivalent to locking their weight to be zero.
  - Equivalent to assigning them gaussian priors with mean zero and variance zero.
  - Dropping low counts does remove the features which were most in need of smoothing…
  - … and speeds up the estimation by reducing model size …
  - … but count cutoffs generally hurt accuracy in the presence of proper smoothing.
- Don't use count cutoffs unless necessary for memory usage reasons. Prefer L_1 regularization for finding features to drop.

Smoothing/Priors/ Regularization for Maxent Models