NEW YORK UNIVERSITY

# Structured Prediction

http://bit.ly/DLSP20

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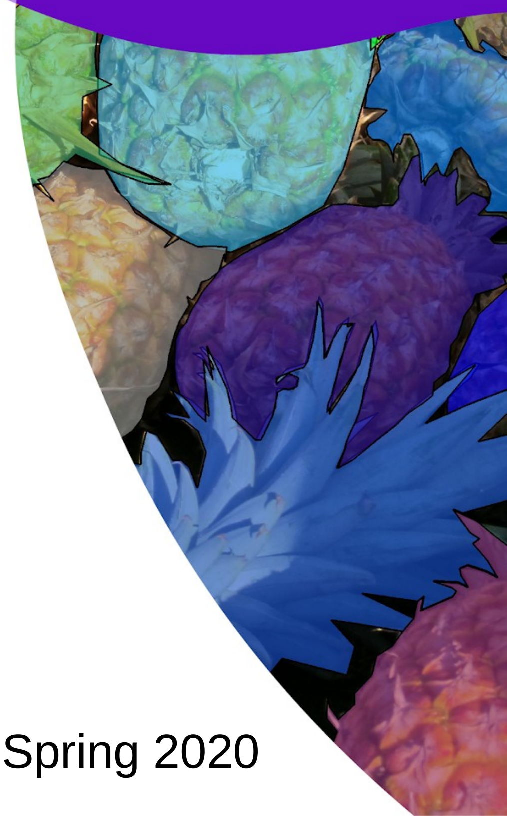


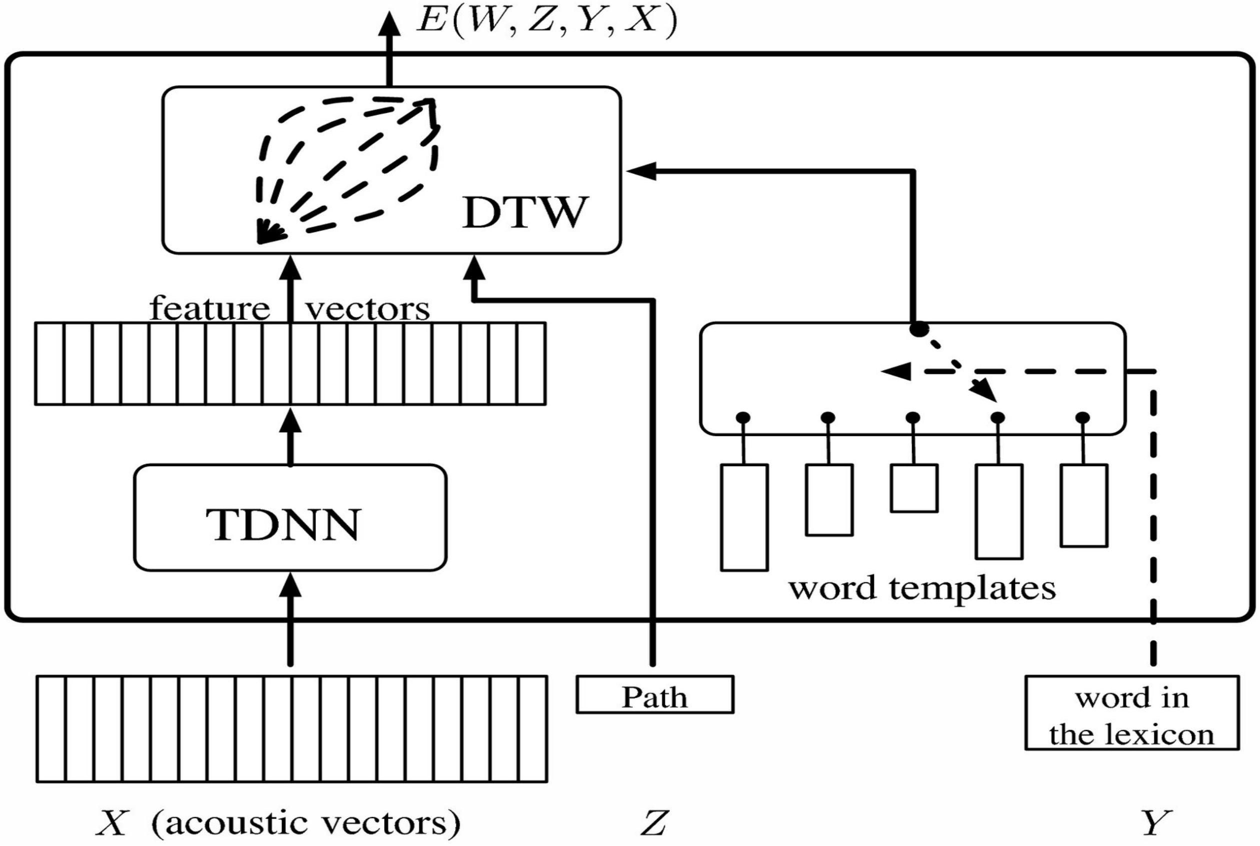
Deep Learning, NYU, Spring 2020

# Structured Prediction

A particular type of latent variable models

# The Oldest Example of Structured Prediction

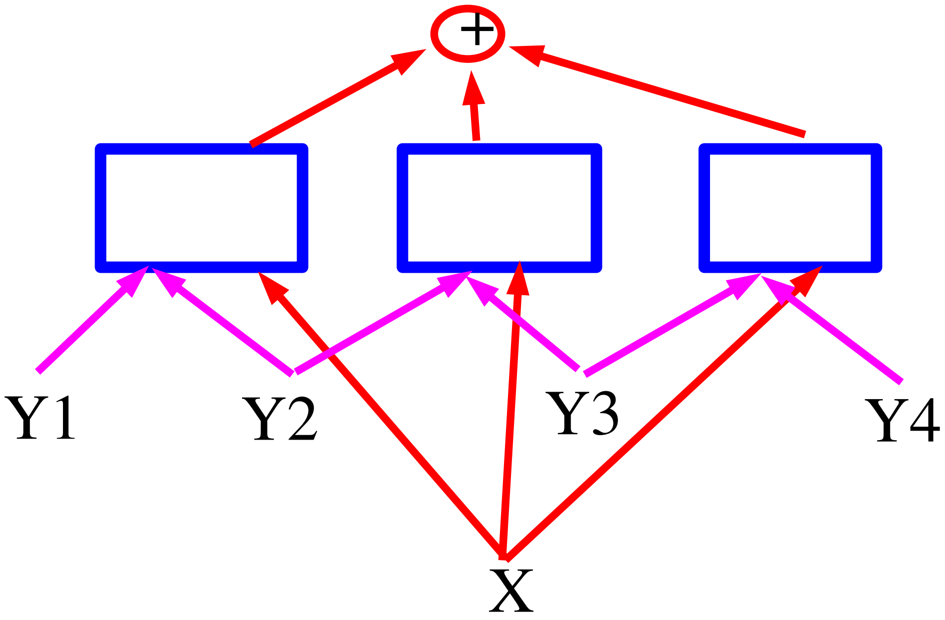
- **Trainable Automatic Speech Recognition system with a convolutional net (TDNN) and dynamic time warping (DTW)**
- **The feature extractor and the structured classifier are trained simultanesously in an integrated fashion.**
- **with the LVQ2 Loss :**
  - Driancourt and Bottou's speech recognizer (1991)
- **with NLL:**
  - Bengio's speech recognizer (1992)
  - Haffner's speech recognizer (1993)



# Energy-Based Factor Graphs: Energy = Sum of "factors"

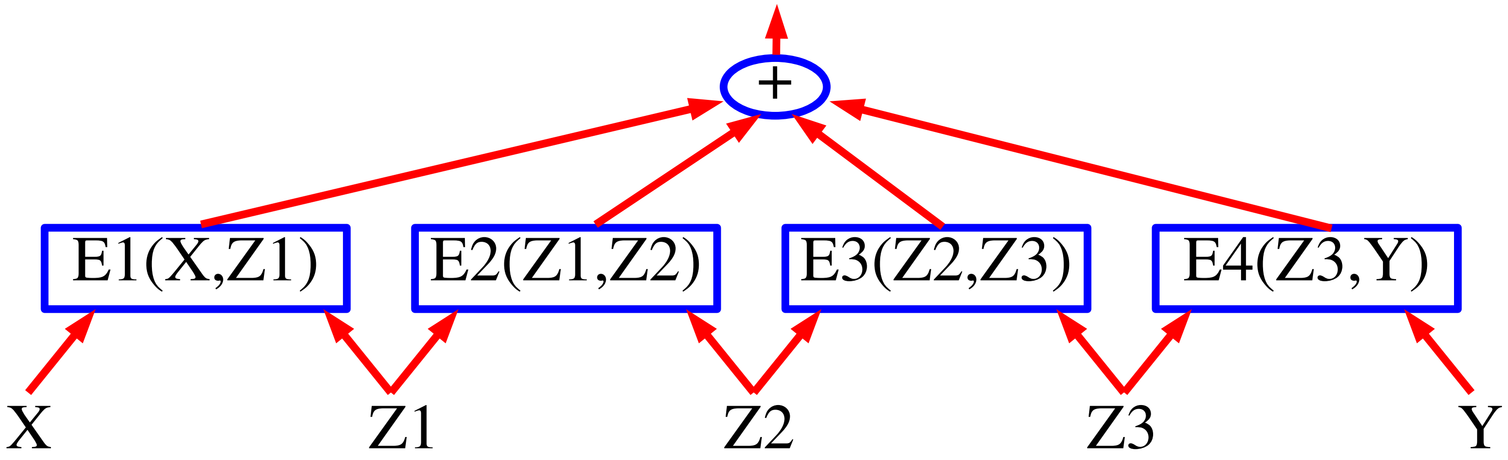
- **Sequence Labeling**
  - Output is a sequence Y1,Y2,Y3,Y4......
  - NLP parsing, MT, speech/handwriting recognition, biological sequence analysis
  - The factors ensure grammatical consistency
  - They give low energy to consistent sub-sequences of output symbols
  - The graph is generally simple (chain or tree)
  - Inference is easy (dynamic programming, min-sum)

$$Y^* = \operatorname{argmin}_{Y \in \mathcal{Y}, Z \in \mathcal{Z}} E(Z, Y, X).$$



# Energy-Based Factor Graphs

- **When the energy is a sum of partial energy functions (or when the probability is a product of factors):**
  - Efficient inference algorithms can be used for inference (without the normalization step).

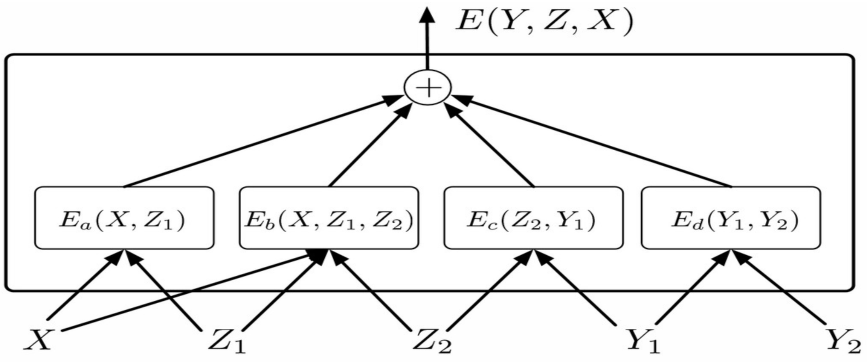


# Efficient Inference: Energy-Based Factor Graphs

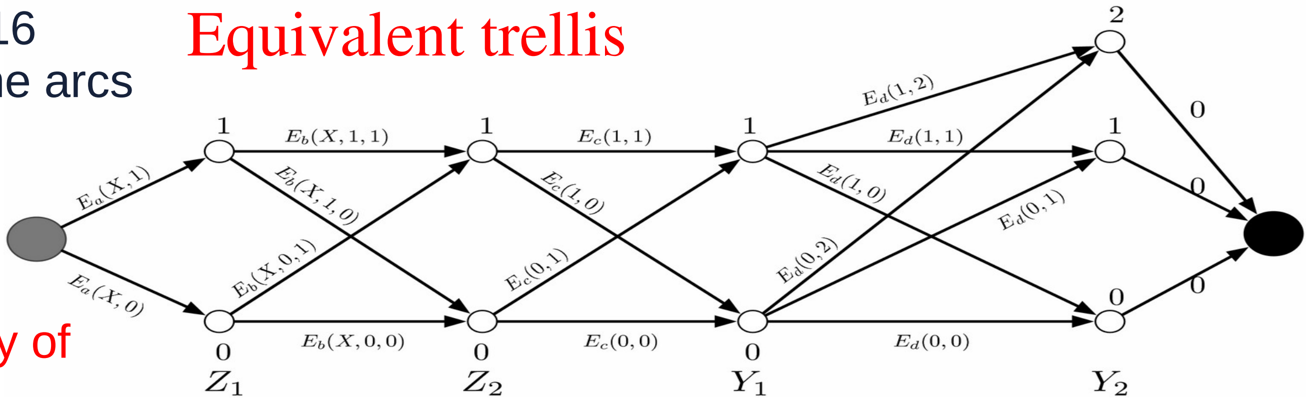
- **Example:**
  - Z1, Z2, Y1 are binary
  - Z2 is ternary
  - A naïve exhaustive inference would require 2x2x2x3=24 energy evaluations (= 96 factor evaluations)
  - BUT: Ea only has 2 possible input configurations, Eb and Ec have 4, and Ed 6.
  - Hence, we can precompute the 16 factor values, and put them on the arcs in a trellis.
  - A path in the trellis is a config of variable
  - The cost of the path is the energy of the config

- **The energy is a sum of "factor" functions**

Factor graph



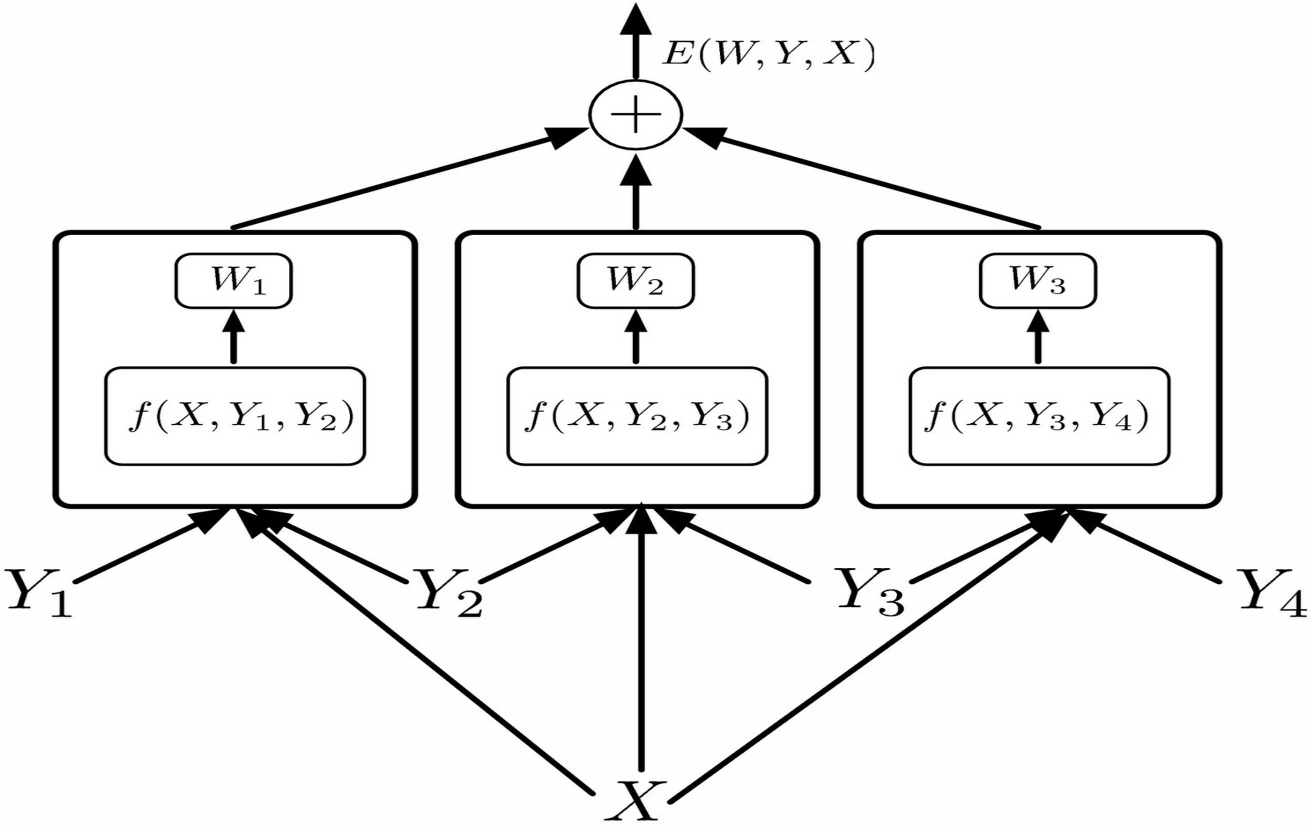

Equivalent trellis



# Simple Energy-Based Factor Graphs with “Shallow” Factors

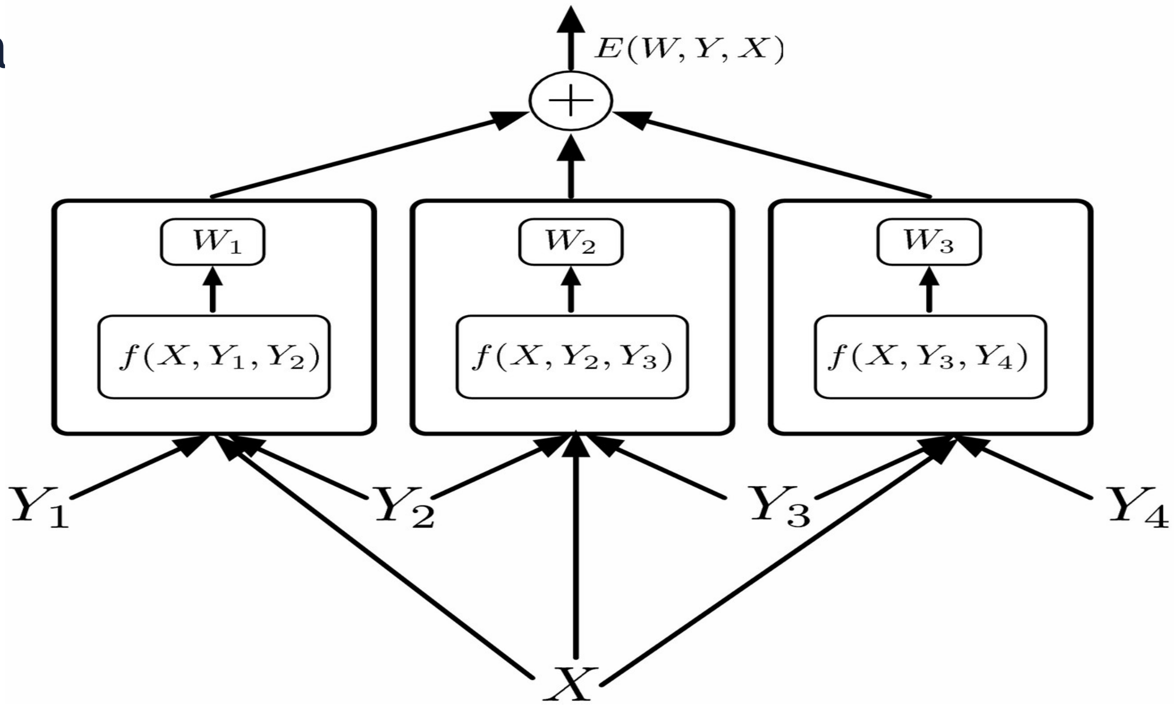
## Linearly Parameterized Factors

- **with the NLL Loss :**
  - Lafferty's **Conditional Random Field**
- **with Hinge Loss:**
  - Taskar and Altun/Hofmann's **Max Margin Markov Nets** and **Latent SVM**
- **with Perceptron Loss**
  - Collins's **Structured Perceptron** model



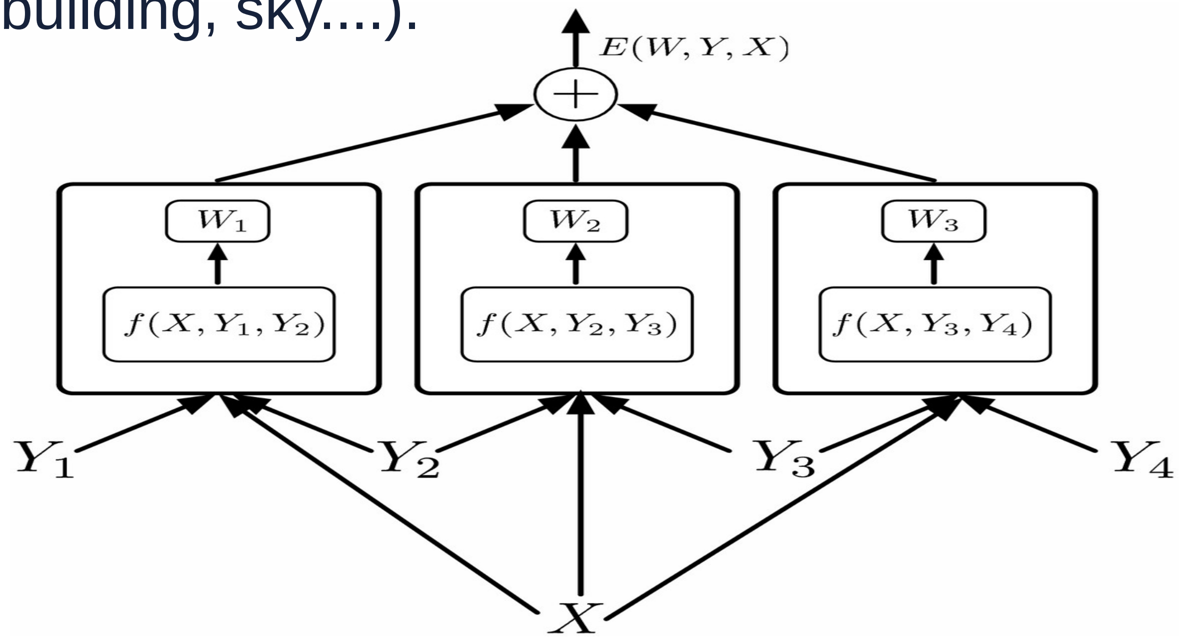
# Example : The Conditional Random Field Architecture

- **A CRF is an energy-based factor graph in which:**
  - the factors are **linear in the parameters (shallow factors)**
  - The factors take neighboring output variables as inputs
  - The factors a



# Example : The Conditional Random Field Architecture

- **Applications:**
  - X is a sentence, Y is a sequence of Parts of Speech Tags (there is one Yi for each possible group of words).
  - X is an image, Y is a set of labels for each window in the image (vegetation, building, sky....).

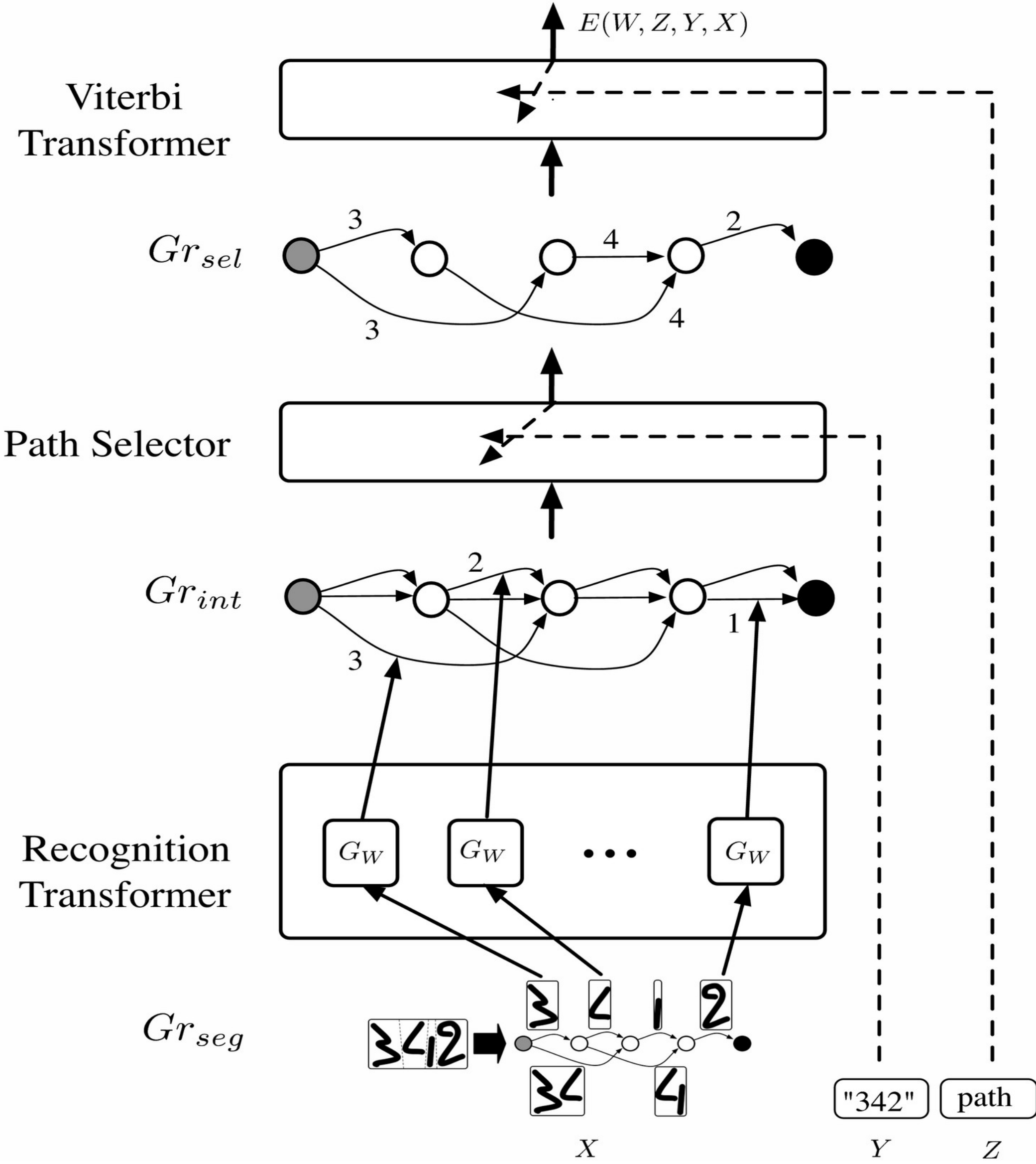


# Deep/non-linear Factors for Speech and Handwriting

- **Trainable Speech/Handwriting Recognition systems that integrate Neural Nets (or other "deep" classifiers) with dynamic time warping, Hidden Markov Models, or other graph-based hypothesis representations**
- **Training the feature extractor as part of the whole process.**
- **with the LVQ2 Loss :**
  - Driancourt and Bottou's speech recognizer (1991)
- **with NLL:**
  - Bengio's speech recognizer (1992)
  - Haffner's speech recognizer (1993)
- **With Minimum Empirical Error loss**
  - Ljolje and Rabiner (1990)
- **with NLL:**
  - Bengio (1992), Haffner (1993), Bourlard (1994)
- **With MCE**
  - Juang et al. (1997)
- **Late normalization scheme (un-normalized HMM)**
  - Bottou pointed out the **label bias problem** (1991)
  - Denker and Burges proposed a solution (1995)

# Deep Factors & implicit graphs: GTN

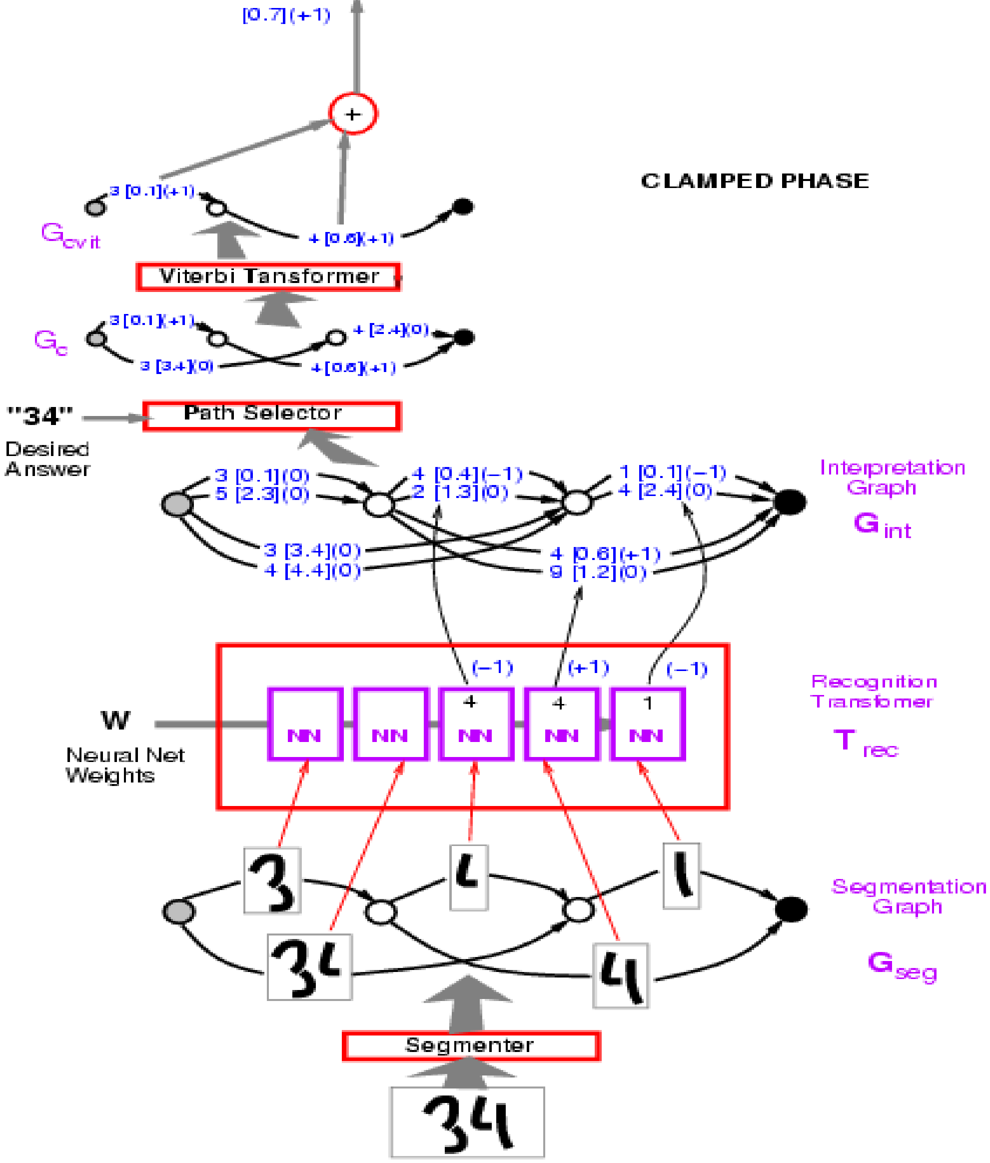
- **Handwriting Recognition with Graph Transformer Networks**
- **Un-normalized hierarchical HMMs**
  - Trained with Perceptron loss [LeCun, Bottou, Bengio, Haffner 1998]
  - Trained with NLL loss [Bengio, LeCun 1994], [LeCun, Bottou, Bengio, Haffner 1998]
- **Answer = sequence of symbols**
- **Latent variable = segmentation**



# Graph Transformer Networks

- **Variables:**
  - X: input image
  - Z: path in the interpretation graph/segmentation
  - Y: sequence of labels on a path
- **Loss function: computing the energy of the desired answer:**

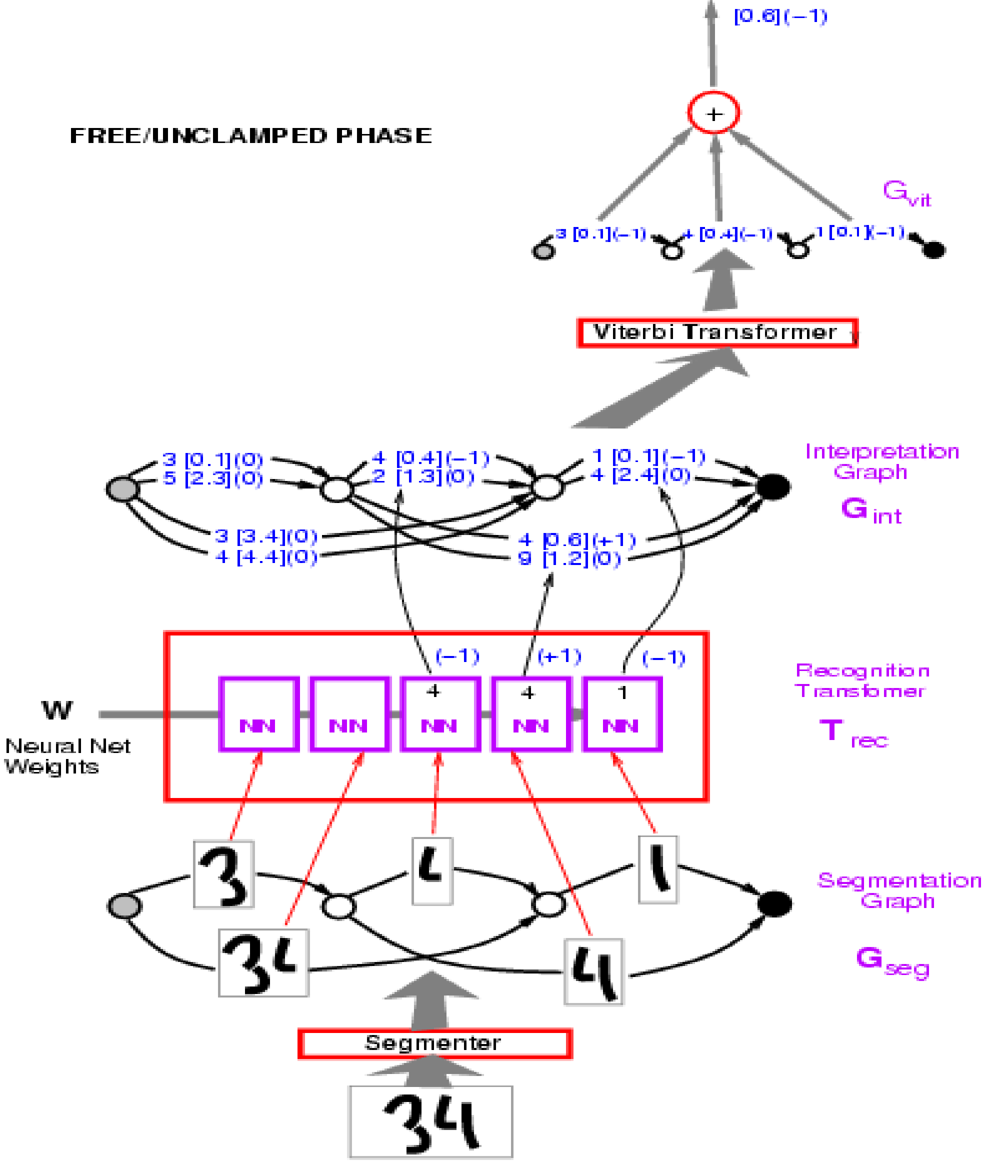
$$E(W, Y, X)$$



# Graph Transformer Networks

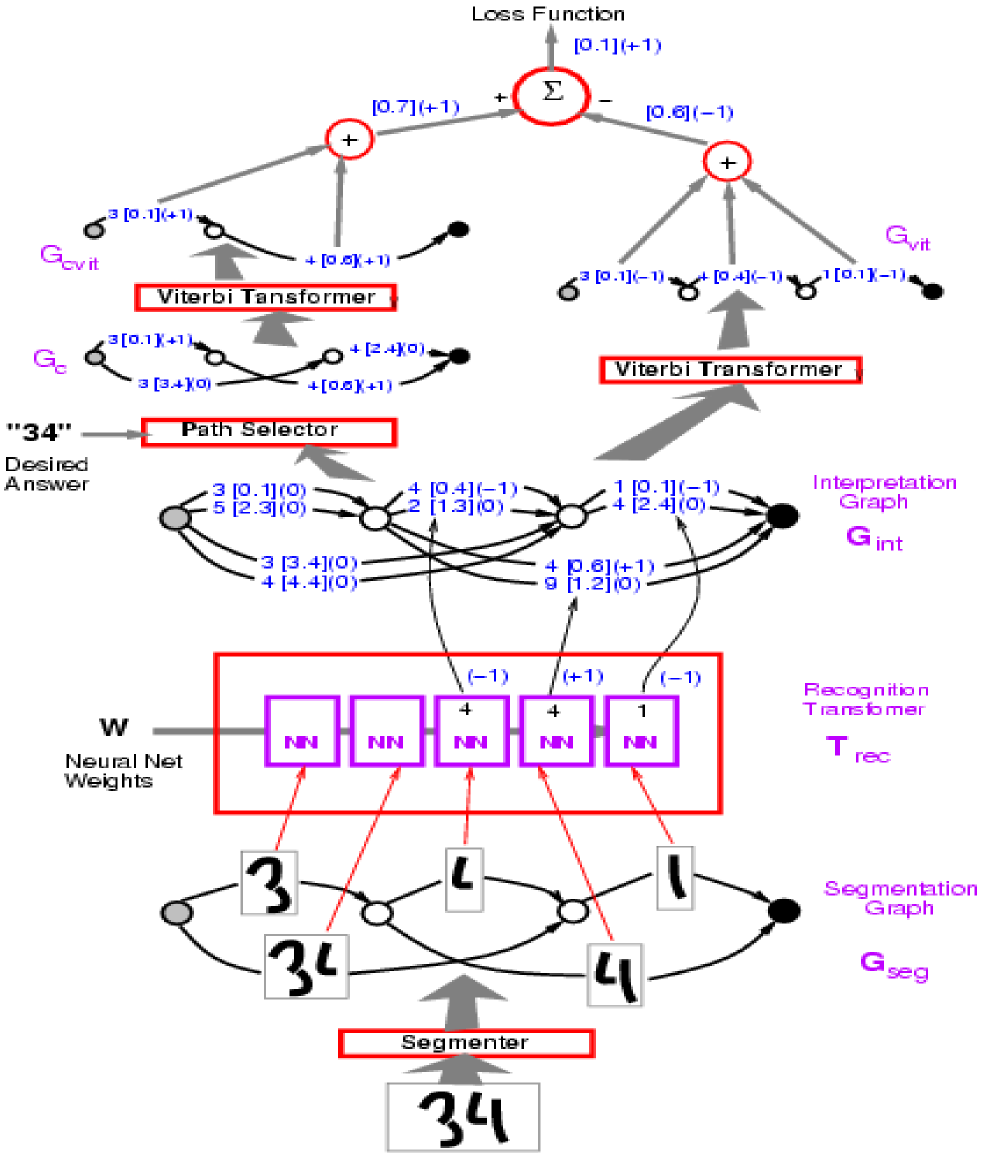
- **Variables:**
  - X: input image
  - Z: path in the interpretation graph/segmentation
  - Y: sequence of labels on a path
- **Loss function: computing the constrastive term:**

$$E(W, \check{Y}, X)$$



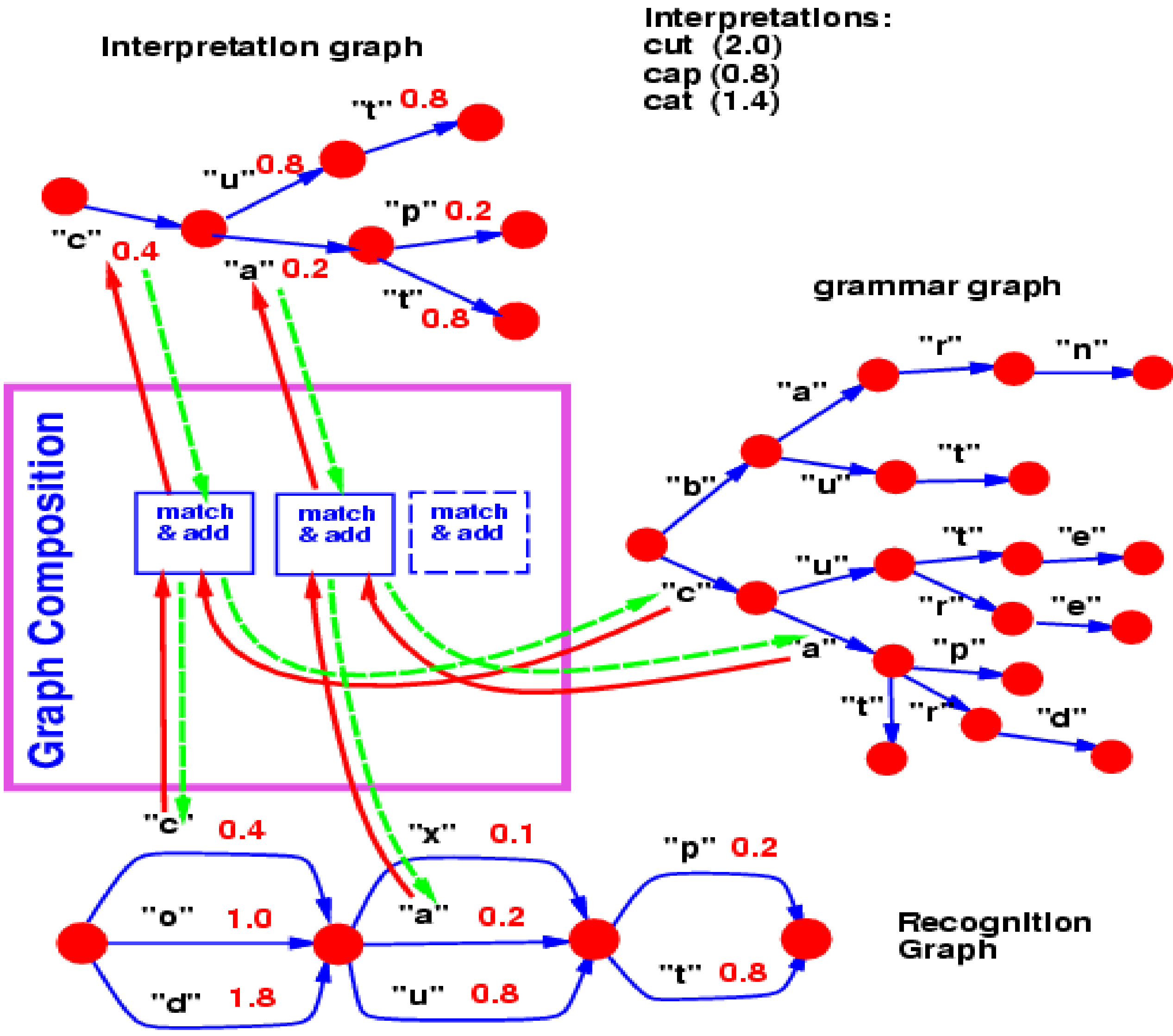
# Graph Transformer Networks

- **Example: Perceptron loss**
- **Loss = Energy of desired answer – Energy of best answer.**
  - (no margin)



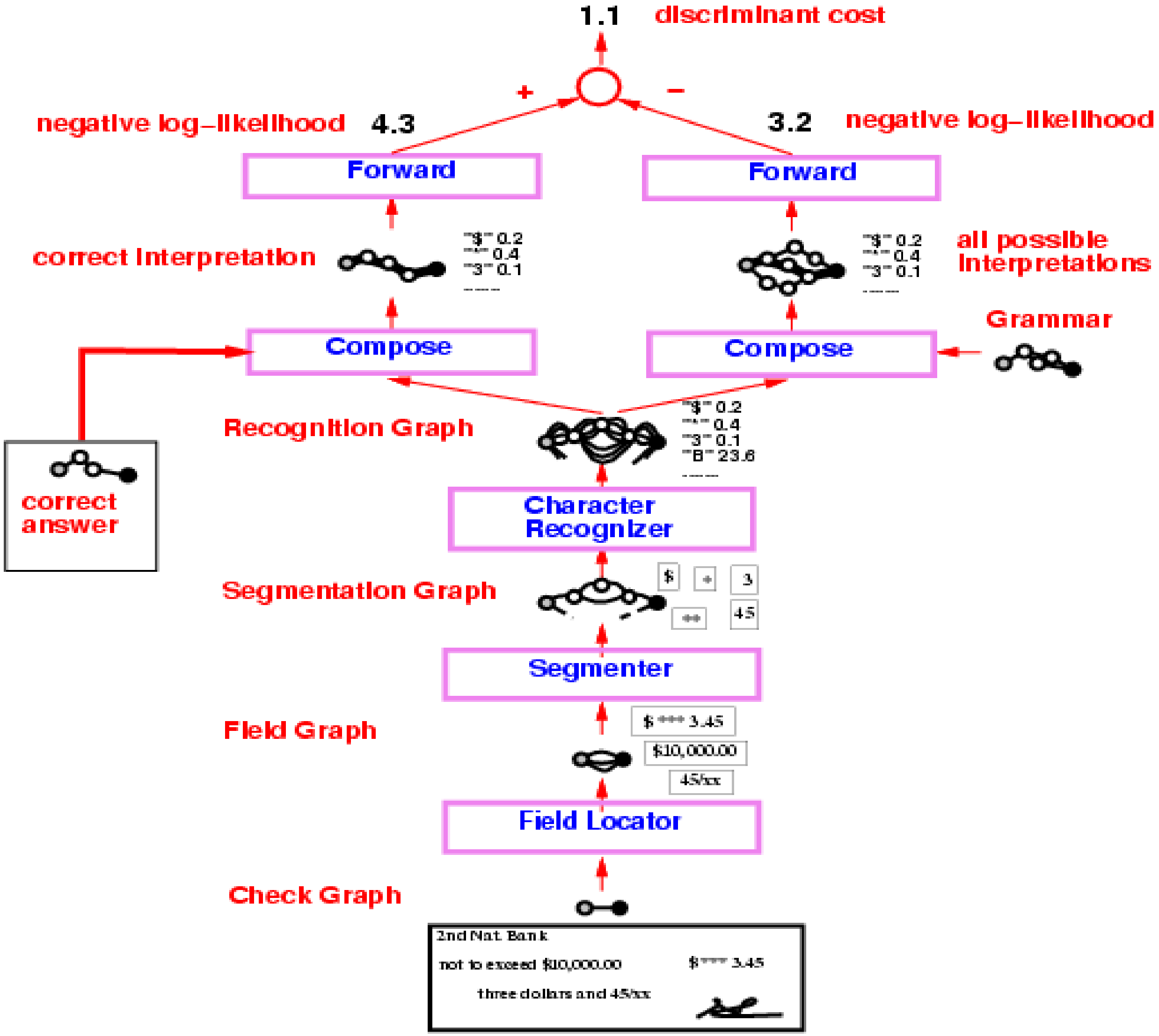
# Graph Composition, Transducers.

- The composition of two graphs can be computed, the same way the dot product between two vectors can be computed.
- General theory: semi-ring algebra on weighted finite-state transducers and acceptors.



# Check Reader

- Graph transformer network trained to read **check amounts.**
- Trained globally with Negative-Log-Likelihood loss.
- 50% percent corrent, 49% reject, 1% error (detectable later in the process.
- **Fielded in 1996**, used in many banks in the US and Europe.
- Processes an estimated **10% of all the checks written in the US.**



# Deep Factors / Deep Graph: ASR with TDNN/HMM

- **Discriminative Automatic Speech Recognition system with HMM and various acoustic models**
  - Training the acoustic model (feature extractor) and a (normalized) HMM in an integrated fashion.
- **With Minimum Empirical Error loss**
  - Ljolje and Rabiner (1990)
- **with NLL:**
  - Bengio (1992)
  - Haffner (1993)
  - Bourlard (1994)
- **With MCE**
  - Juang et al. (1997)
- **Late normalization scheme (un-normalized HMM)**
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# What Make a “Good” Loss Function

## Good and bad loss functions

| Loss (equation #) | Formula | Margin |
|---|---|---|
| energy loss | $E(W, Y^i, X^i)$ | none |
| perceptron | $E(W, Y^i, X^i) - \min_{Y \in \mathcal{Y}} E(W, Y, X^i)$ | 0 |
| hinge | $\max\left(0, m + E(W, Y^i, X^i) - E(W, \bar{Y}^i, X^i)\right)$ | $m$ |
| log | $\log\left(1 + e^{E(W,Y^i,X^i) - E(W,\bar{Y}^i,X^i)}\right)$ | $> 0$ |
| LVQ2 | $\min\left(M, \max(0, E(W, Y^i, X^i) - E(W, \bar{Y}^i, X^i)\right)$ | 0 |
| MCE | $\left(1 + e^{-\left(E(W,Y^i,X^i) - E(W,\bar{Y}^i,X^i)\right)}\right)^{-1}$ | $> 0$ |
| square-square | $E(W, Y^i, X^i)^2 - \left(\max(0, m - E(W, \bar{Y}^i, X^i))\right)^2$ | $m$ |
| square-exp | $E(W, Y^i, X^i)^2 + \beta e^{-E(W,\bar{Y}^i,X^i)}$ | $> 0$ |
| NLL/MMI | $E(W, Y^i, X^i) + \frac{1}{\beta} \log \int_{y \in \mathcal{Y}} e^{-\beta E(W,y,X^i)}$ | $> 0$ |
| MEE | $1 - e^{-\beta E(W,Y^i,X^i)} / \int_{y \in \mathcal{Y}} e^{-\beta E(W,y,X^i)}$ | $> 0$ |