

Intro
Hypergraph View: Computation graph = labeled acyclic **hypergraph**. Edges can have multiple sources/targets. **Complexity:** same time as f ; space higher (store intermediates) vec-vec: $O(d)$; mat-vec: $O(nm)$; mat-mat: $O(nml)$
NLL $\nabla = \mathbf{0}$: $\sum_{i=1}^n \mathbf{f}(x_i, y_i) = \sum_{i=1}^n \mathbb{E}_{y|x_i, \theta}[\mathbf{f}(x_i, y)]$ Observed features = Expected features **Hessian:** $\mathbf{H} = \sum_{i,j} \text{Cov}_{y|x_i, \theta}[\mathbf{f}(x_i, y)]$ (PSD!)

1. Backpropagation
Chain Rule: $\frac{d}{dx}[f(g(x))] = f'(g(x))g'(x)$ **Jacobian:** $f: \mathbb{R}^n \rightarrow \mathbb{R}^m, \frac{dy}{dx} = \begin{bmatrix} \frac{dy_1}{dx_1}, \dots, \frac{dy_n}{dx_n} \end{bmatrix} \in \mathbb{R}^{m \times n}$ **Multivar:** $\frac{dy_i}{dx_j} = \sum_{k=1}^m \frac{dy_i}{dz_k} \frac{dz_k}{dx_j}$

Bauer Path Formula: $\frac{dy_i}{dx_j} = \sum_{p \in \mathcal{P}(j,i)} \prod_{(k,l) \in p} \frac{dz_l}{dx_k}$
 $\mathcal{P}(j,i)$ =all paths $j \rightarrow i$; worst $O(m^n)$ **Computation Graph:** DAG w/ function nodes, edges=variable flow

Forward vs Reverse: **Forward:** expand $\frac{d}{dx}$ recursively, same flow as fwd **Reverse:** 2 passes—fwd compute vals, bwd compute grads **Complexity:** same time as f ; higher space (store intermediates)

Primitives: Sum: $\frac{d(a+b)}{da} = 1$; Prod: $\frac{d(ab)}{da} = b$

2. Log-Linear Models
Prob Basics: Bayes: $p(y|x) = \frac{p(x|y)p(y)}{\int p(x|y)p(y)dy}$ **Marginal:** $p(x) = \sum_y p(x, y)$ **Expectation:** $\mathbb{E}[f(x)] = \sum_x f(x)p(x)$

Log-Linear Model: $p(y|x, \theta) = \frac{\exp(\theta \cdot f(x, y))}{Z(\theta)}, Z(\theta) = \sum_{y' \in Y} \exp(\theta \cdot f(x, y'))$ $\log p(y|x, \theta) = \theta \cdot f(x, y) - \log Z$ (linear in log space!) **Discrete MLE:** $p(y|x) = \frac{\text{count}(x, y)}{\text{count}(x)}$ (sparse 问题)

MLE ∇ : $\theta_{\text{MLE}} = \arg \min_{\theta} - \sum_{n=1}^N \log p(y_n|x_n, \theta)$ $\frac{d\mathcal{L}}{d\theta_k} = - \sum_n f_k(x_n, y_n) + \sum_n \sum_{y'} p(y'|x_n; \theta) f_k(x_n, y')$ 观测特征计数 = 期望特征计数 \rightarrow **Expectation Matching**

Softmax: $\text{softmax}(h, y, T) = \frac{\exp(h_y/T)}{\sum_{y'} \exp(h_{y'}/T)}$ $T \rightarrow 0$: argmax; $T \rightarrow \infty$: uniform $\log \text{softmax} = h_y - \log \sum_{y'} \exp(h_{y'})$ (logsumexp) $\frac{d \log \text{softmax}}{d\theta} = f(x, y) - \sum_i \text{softmax}(\theta^\top f, i) f(x, i)$

MLP Architecture: Problem: Log-linear needs linearly separable data **Solution:** Learn non-linear feature fn $h_k = \sigma_k(W_k^\top h_{k-1}), h_1 = \sigma_1(W_1^\top e(x))$ Output: $\text{softmax}(\theta^\top h_n)$

Sigmoid & Activations: $\sigma(x) = \frac{1}{1 + \exp(-x)}, \nabla \sigma = \sigma(1 - \sigma)$ **tanh:** $\frac{1-e^{-2x}}{1+e^{-2x}}, \nabla = 1 - \tanh^2$, Sigmoid/tanh, vanishing gradient \rightarrow use ReLU **Backprop(MLP):** $\frac{\partial \ell}{\partial W_k} = \frac{\partial \ell}{\partial y} \frac{\partial y}{\partial h_n} (\prod_{m=k+1}^n \sigma'_m W_m) \sigma'_k h_{k-1}$

Learning Pipeline: Embedding \rightarrow Pooling (sum/mean/max) \rightarrow NN \rightarrow Softmax

Exp Family & MaxEnt: $p(x|\theta) = \frac{1}{Z(\theta)} h(x) \exp(\theta \cdot \varphi(x))$
Max Entropy: $H(p) = - \sum_x p(x) \log p(x)$ 选最大熵分布=最少假设=Laplace 原则

3. Language Models
Structured Prediction: Kleene V^* : infinite set of finite-length strings from V **Language Model:** weighted prefix tree, each sentence=unique path $p(y) = \frac{1}{Z} \prod_{t=1}^{|y|} \text{weight}_{y_{\leq t}}$

Local Normalization: $Z = 1$ when children edges sum to 1 at each node **Consistency:** $p(\text{EOS}|y_{<t}, V^*) > \varepsilon > 0$ $p(|y| = \infty) \leq \lim_{t \rightarrow \infty} (1 - \varepsilon)^t = 0$ (tight)

N-gram Model: $p(y_t|y_{<t}) = p(y_t|y_{t-1}, \dots, y_{t-n+1}) = \frac{\exp(w_{y_t, h_t})}{\sum_{y' \in V} \exp(w_{y', h_t})}, h_t \in \mathbb{R}^d$ **Bengio:** $h_t = f(e(\text{hist}))$, $e(\text{hist}) = [e(y_{t-1}); e(y_{t-2}); \dots]$

RNN: $h_t = f(h_{t-1}, e(y_{t-1}))$ (implicit infinite context) **Vanilla:** $h_t = \sigma(W_1 h_{t-1} + W_2 e(y_{t-1}))$ **BPTT:** unroll through time, sum grads over timesteps

4. Word Embeddings
Encoding: One-hot: $v \in O(|V|)$, only word=1 **Bag-of-words:** pooled one-hot (sum/mean/max) **N-grams:** vectors huge—every combo needs slot

Skip-gram: Preprocess: word-context pairs ($k \times C$ many), window k $p(c|w) = \frac{1}{Z(w)} \exp(e_{\text{word}(w)} \cdot e_{\text{ctx}(c)})$, $O(2|V|k)$ params **Bilinear:** linear if all-but-one vars held constant **Similarity:** $\cos(u_i, u_j)$

5. CRF & POS Tagging
As Graph: Fully connected graph w/ POS-tag nodes per layer $\text{score}(\langle D, N, V, \dots \rangle, w) = \theta f(t, w)$ Problem: $O(|\mathcal{T}|^N)$ paths in normalizer

CRF Model: $p(t|w) = \frac{\exp(\text{score}(t, w))}{\sum_{t' \in \mathcal{T}} \exp(\text{score}(t', w))}$
Decom-position: $\text{score}(t, w) = \sum_{n=1}^N \text{score}(\langle t_{n-1}, t_n \rangle, w, n)$
 $p(t|w) \propto \prod_{n=1}^N \exp\{\text{score}(\langle t_{n-1}, t_n \rangle, w)\}$
Forward-Backward DP: $\forall t_n: \beta(w, t_n, N) \leftarrow 1$ for $n \leftarrow N-1, \dots, 0$: $\beta(w, t_n, n) \leftarrow \sum_{t_{n+1} \in \mathcal{T}} \exp(\text{score}) \times \beta(w, t_{n+1})$

Viterbi Decoding: $\beta(w, t_n) \leftarrow \max_{t_{n+1}} \exp(\text{score}) \times \beta(w, t_{n+1})$ **Structured CRF:** $\log p = \sum_i (\text{score}(t^{(i)}, w^{(i)}) - \max_{t'} \text{score}(t', w^{(i)}))$

DP 推导: Goal: $Z = \sum_t \exp \text{score}(t, w)$ **Step1:** 可加分解 $\text{score} = \sum_n \text{score}_n$ **Step2:** $Z = \sum_t \prod_n \exp \text{score}_n = \sum_{t_1} \exp \text{score}_1 \times (\sum_{t_2} \dots)$ (distrib!) $O(|\mathcal{T}|^N) \rightarrow O(N|\mathcal{T}|^2)$ **若依赖 3-gram:** $O(N|\mathcal{T}|^3)$

Common Semirings:

Name	\mathbb{K}	\oplus	\otimes	0	1	用途
Real	$\mathbb{R}_{\geq 0}$	+	\times	0	1	Z partition fn
Viterbi	$\mathbb{R} \cup \{-\infty\}$	max	+	$-\infty$	0	最优 path/解码
Log	$\mathbb{R} \cup \{\pm\infty\}$	lse	+	$-\infty$	0	$\log Z$ 数值稳定
Boolean	$\{0, 1\}$	\vee	\wedge	0	1	可达性/存在性
Counting	\mathbb{N}	+	\times	0	1	路径数/歧义度
Tropical	$\mathbb{R} \cup \{\infty\}$	min	+	∞	0	最短路/编辑距离

Semiring Definition: $\langle \mathbb{K}, \oplus, \otimes, \mathbf{0}, \mathbf{1} \rangle$ where:
1. $(\mathbb{K}, \oplus, \mathbf{0})$: **comm monoid** (assoc+comm+identity)
2. $(\mathbb{K}, \otimes, \mathbf{1})$: **monoid** (assoc+identity)
3. **Distrib:** $(x \oplus y) \otimes z = (x \otimes z) \oplus (y \otimes z)$
4. **Annihilator:** $\mathbf{0} \otimes x = x \otimes \mathbf{0} = \mathbf{0}$

Semiring 意义: ϕ : 分治 (split) points 合并, OR/MAX/+) \otimes : 连接 (左右子树组合, AND/ \times / $+$) 0: 吸收元, 消除 invalid; 1: 单位元, null 不破坏

Monoid 判定:
1. **Closure:** $a \otimes b \in \mathbb{K}$; 2. **Assoc:** $(a \otimes b) \otimes c = a \otimes (b \otimes c)$; 3. **Identity:** $\exists e: a \otimes e = e \otimes a = a$

Semiring 判定:
1. \oplus -monoid (comm): $a \oplus b = b \oplus a$; 2. \otimes -monoid; 3. Distributivity (左右皆需); 4. Annihilation: $\mathbf{0} \otimes x = \mathbf{0}$ **陷阱:** $\mathbf{0} = 1$ 必失败!
Closed Semiring & Kleene*: $a^* = \bigoplus_{n=0}^{\infty} a^{\otimes n} = \mathbf{1} \oplus a \otimes a^*$ Real 上 $|a| < 1$: $a^* = \frac{1}{1-a}$ (geometric series) 用于 globally normalized LM

6. CFG Parsing
Constituents: Multi-word units as single unit **Tests:** Pronoun substitution, Clefting, Answer ellipsis Ambiguity: PP attachment, modifier scope

CFG Definition: $G = \langle N, \mathcal{S}, \Sigma, \mathcal{R} \rangle$ Non-terminals, start symbol, terminals, production rules CNF: $N_1 \rightarrow N_2 N_3$ or $N \rightarrow a$; $O(4^N)$ trees

Weighted CFG: Global: $p(t) = \frac{1}{Z} \prod_{r \in t} \exp(\text{score}(r))$ $Z = \sum_{t' \in \mathcal{T}} \prod_{r'} \exp(\text{score}(r'))$ (可能 ∞ !) **Probabilistic:** local norm $\sum_k p(\alpha_k|N) = 1$

CKY Algorithm: $O(N^3|R|)$, needs CNF for $n = 1, \dots, N$: for $X \rightarrow s_n \in \mathcal{R}$: chart $[n, n+1, X] \oplus \exp(\text{score}(X \rightarrow s_n))$ for span=2, ..., N : for $i = 1, \dots, N$ - span: $k \leftarrow i$ + span; for $j = i+1, \dots, k-1$: for $X \rightarrow YZ \in \mathcal{R}$: chart $[i, k, X] \oplus \exp\{\text{score}\} \otimes \text{chart}[i, j, Y] \otimes \text{chart}[j, k, Z]$ **Best parse:** semiring (max, +)

7. Dependency Parsing
Dependency Tree: Directed spanning tree, root degree 1 **Projective:** no crossing arcs (\approx constituency w/ heads) **Non-projective:** crossing arcs (\approx discontinuous constituents) # spanning trees: $O((n-1)^{n-2})$

Edge-Factored Model: $p(t|w) = \frac{1}{Z} \prod_{(i \rightarrow j) \in t} \exp(\text{score}(i, j, w)) \exp(\text{score}(r, w))$
Edge factor assumption: score factors over edges
Matrix-Tree Theorem: $A_{ij} = \exp(\text{score}(i, j, w))$, $\rho_j = \sum_{i=1}^n A_{i,j}$
 $\exp(\text{score}(j, w)) Z = \det(L)$ where $L_{ij} = \begin{cases} \rho_j & i=j \\ \sum_{i' \neq j} A_{i',j} & \text{else} \\ -A_{ij} & \end{cases}$
Computing det in $O(n^3)$

MST Decoding: $\arg \max_{t \in \mathcal{T}} \sum_{(i \rightarrow j) \in t} \text{score}(i, j, w)$
Algo: max incoming edge, contract cycles (update weights) **Root Constraint:** for each root edge, compute removal cost; remove cheapest Runtime: $O(n^2)$

8. Semantic Parsing
Syntax vs Semantics: Syntax: structural org (parse tree) **Semantics:** underlying meaning **Logical form:** quantifiers, vars, boolean, predicates

Lambda Calculus: Abstraction: M term, x var $\rightarrow \lambda x.M$ term **Application:** M, N terms $\rightarrow MN$ term **β -reduction:** $(\lambda x.M)N = M[x := N]$ **β -infinity:** $F = \lambda x((xx)x), FF = ((FF)F) = \dots$

Composition: $S_{VP} \rightarrow NP$ VP, $S_{\text{sem}} = \text{VP.sem}(\text{NP.sem})$ **Compositionality:** meaning of whole = fn of parts

Combinatory Logic: I: $Ix = x$; K: $Kxy = x$; S: $Sxyz = (xz)(yz)$ S-K calculus = lambda calculus (via translator T) Don't need I: $(SKK)x = x$

9. WFSTs
Transducer: $T = \langle Q, \Sigma, \Omega, \lambda, \rho, \delta \rangle$ States, input vocab, output vocab, initial/final scores, transitions Goal: $p(y|x), x \in \Sigma^*, y \in \Omega^*$

Scoring: $\text{score}(\pi) = \lambda(q_{\text{start}}) + \sum_n \delta(q_n) + \rho(q_{\text{end}})$ $p(y|x) = \frac{1}{Z} \sum_{\pi \in \Pi(x, y)} \exp(\text{score}(\pi))$ $Z = \sum_{y' \in \Omega^*} \sum_{\pi'} \exp(\text{score})$ (infinite—loops!)

Floyd-Warshall & Semiring: $\forall i, j, k: \text{dist}[i][j] \leftarrow \text{dist}[i][j] \oplus (\text{dist}[i][k] \otimes \text{dist}[k][j])$ **Matrix mult:** $\text{sum} \leftarrow \bar{0}$; $\text{sum} \leftarrow \text{sum} \oplus (A[n][m] \otimes B[m][p])$

Kleene Star: $W^* = \bigoplus_{k=0}^{\infty} W^k = I + WW^* \Leftrightarrow W^* = (I - W)^{-1}$
Warshall-Floyd-Kleene: $\text{dist}[i][j] \leftarrow \text{dist}[i][j] \oplus (\text{dist}[i][k] \otimes \text{dist}[k][j])$

10. Transformers & MT
Seq2Seq: $z = \text{encoder}(x), y|x \sim \text{decoder}(z)$ $p(y|x) = \prod_{t=1}^p p(y_t|x, y_1, \dots, y_{t-1})$ Optimize log-likelihood

Attention: $\alpha^T V = \sum_i \alpha_i v_i^T$ (soft retrieval) $\alpha_i = \text{softmax}(\text{score}(q, k_i))$ $K = V = H^{(e)}, q_t = h_t^{(d)}, c = \alpha^T V$

Transformer Components: Word Embed: token \rightarrow vector **Positional Embed:** encode word position (no recurrence!) **Residual Connections:** mitigate vanishing ∇ s **Layer Norm:** normalize layer inputs **Self-attention:** Q, K, V from same sequence

Decoding: $y^* = \arg \max_{y \in Y} \text{score}(x, y)$ W/o assumptions: $O(|\Sigma|^{n_{\text{max}}})$ paths **Beam Search:** keep k best at each step (greedy approx) **Sampling:** sample from $p(y|x)$ each step **Eval:** BLEU (n-gram overlap), METEOR

11. Modeling Choices
Prob vs Non-Prob: Prob: leverage prob theory, needs assumptions CRF, RNN, N-gram models **Non-Prob:** interpretable, uncertainty unclear Perceptron, SVM, CFG rules
Disc vs Generative: Discriminative: model boundary $p(y|x)$ **Generative:** model own dist $p(x, y)$

Local vs Global Norm: Local: efficient train, biased predictions **Global:** needs Z , unbiased Independence assumptions control complexity

Loss & Regularization: LogLoss: $\ell(y, y') = \log(1 + e^{-y \cdot y'})$ **Exp-Loss:** $\ell(y, y') = e^{-y \cdot y'}$ **L1/L2:** weight penalties (Laplace/Gaussian prior)

Evaluation Metrics: Prec: $P_{\text{true}}/P_{\text{all}}$; **Recall:** $P_{\text{true}}/(P_{\text{true}} + N_{\text{false}})$ **Acc:** $(P_{\text{true}} + N_{\text{true}})/N$ **F-score:** $\frac{(1+\beta^2)(\text{prec} \cdot \text{recall})}{\beta^2 \text{prec} + \text{recall}}$

Statistical Tests: $p = 2 \min(P(T \geq t|H_0), P(T \leq t|H_0))$; Rej if $p < \alpha$ **Power:** $P(\text{reject } H_0|H_1)$ **Multiple tests:** $P(\{\text{FalseRej}\} > 0) = 1 - (1 - \alpha)^K$ **Bonferroni:** $\alpha^* = \alpha/K$

Permutation Test: p^* from original data; permute labels k times p-value= $(|\{i: p_i \leq p^*\}| + 1)/(k + 1)$

McNemar's Test: $\chi^2 = \frac{(b-c)^2}{b+c} \sim \chi_1^2$ for $b, c \geq 25$ $H_0: p_b = p_c$; b =C1 wrong/C2 right

5 \times 2cv Test: $\bar{p} = (p^{(1)} + p^{(2)})/2$ $s^2 = (p^{(1)} - \bar{p})^2 + (p^{(2)} - \bar{p})^2$ $t = \left(p_1^{(1)}\right) / \sqrt{1/5 \sum s_i^2} \sim t^5$

12. Bias & Fairness
Bias Sources: Labeling: reproduce annotator bias **Sample selection:** training fits certain profile **Task definition:** excludes certain groups **Imbalanced test:** loss ignores minorities

Ethical Frameworks: Consequentialism: best consequence **Utilitarianism:** hedonistic/preference/welfare **Deontology:** rules must be kept **Social Contract:** natural equality **Anti-subordination:** positive discrimination for equality

Quick Ref Chain: $\frac{d}{dx}[f(g(x))] = f'(g)g'(x)$; Bauer: sum over all paths **Softmax:** $\exp(h_{y_i}) / (\sum \exp(h_{y_j}))$; $T \rightarrow 0$ =argmax; $T \rightarrow \infty$ =uniform **Log-Linear:** $p(y|x) = \exp(\theta \cdot f)/Z$; MLE matches expected features **CRF:** decompose score \rightarrow DP; semiring unifies algos **Viterbi:**

max instead of sum; decoding= $\arg \max$ score **CKY**: $O(N^3|R|)$; needs
CNF; semiring for best/count/prob **Dep Parse**: Matrix-Tree for Z
in $O(n^3)$; MST+contract cycles **Attention**: $\alpha = \text{softmax}(QK^T)$; $c =$
 αV (soft lookup) **WFST**: Kleene* for infinite sums; $(I - W)^{-1}$
Lambda: β -reduction $(\lambda x.M)N = M[x := N]$ **Local vs Global**: bias
vs intractability tradeoff **Semirings**: Boolean/Viterbi/Inside/Tropical/
Counting **Stats**: Bonferroni α/K ; McNemar $(b - c)^2/(b + c)$

Abbrev **BOS/EOS**: Begin/End of Sentence; **CCG**: Combinatory Catego-
rial Grammar; **CFG**: Context-Free Grammar; **CKY**: Cocke-Kasami-Younger;
CNF: Chomsky Normal Form; **CRF**: Conditional Random Field; **DP**: Dy-
namic Programming; **LLM**: Log-Linear Model; **MLE**: Max Likelihood Est;
MST: Min Spanning Tree; **NLP**: Natural Language Processing; **POS**: Part-
of-Speech; **RNN**: Recurrent Neural Network; **WFST**: Weighted Finite State
Transducer;