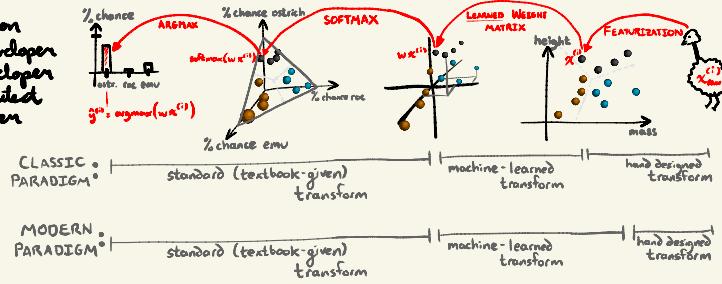


# SOFTMAX @ 5 LEVELS OF SOPHISTICATION

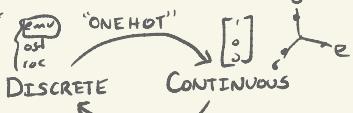
SAM'S EXPLAINERS  
2022-06-07

- A. lay person
- B. MFBT developer
- C. FBR developer
- D. deep architect
- E. researcher



**A. lay person** SOFTMAX is... how we pick 'the' best answer while being fair about ties

models uncertainty: key to learning<sup>a</sup> to calibrated predictions



allows continuous methods to solve discrete tasks

$$\begin{bmatrix} \text{die?} \\ \text{not die?} \end{bmatrix} \xrightarrow{\text{SM}} \begin{bmatrix} 3.5 \\ -1.0 \end{bmatrix}$$

**B. MFBT developer** SOFTMAX is... how we normalize real-valued scores to probabilities

$$\text{softmax}: \mathbb{R}^k \rightarrow \{(p_i : 0 \leq p_i \leq k) \in \mathbb{R}^k : (\forall i : 0 \leq p_i \leq 1) \wedge (\sum_i p_i = 1)\} \subseteq \mathbb{R}^k$$

$$(z_i : 0 \leq z_k) \mapsto \left( \frac{\exp(z_i)}{\sum_j \exp(z_j)} : 0 \leq z_k \right)$$

$$\begin{aligned} z &= \text{np.matmul}(w, x[i]) & \text{dl_dp} &= (-1/p) \cdot y[i] & \text{one-hot} \\ e &= \text{np.exp}(z) & \text{dl_dn} &= -\text{np.dot}(\text{dl_dp}, e/n^2) \\ n &= \text{np.sum}(e) & \text{dl_de} &= \text{dl_dp}/n + \text{dl_dn} \\ p &= e/n & \text{dl_dz} &= p \cdot y[i] \\ & & \text{dl_dz} &= \text{dl_de} \cdot e \\ & & \text{dl_dw} &= \text{np.outer}(\text{dl_dz}, x[i]) \\ & & \text{dl_dw} &= \dots \end{aligned}$$

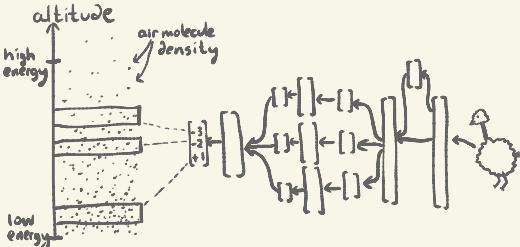
**C. FBR developer** SOFTMAX is... a computationally convenient interface w/ likelihood loss convex, so easy to optimize bounded gradients (despite miracle sensitivity) tight surrogate for 0-1 loss

$$\text{decision func} = \underbrace{(-y^{(i)} w \cdot x^{(i)})}_{\text{trespass}}$$

$$\text{hinge loss} = \max(0, 1 - \dots)$$

$$\text{softplus loss} = \log(1 + \exp(\dots)) = \log\left(\frac{\exp(-\dots)}{1 + \exp(-\dots)}\right) = \log \text{softmax}\left[\frac{\dots}{0}\right]$$

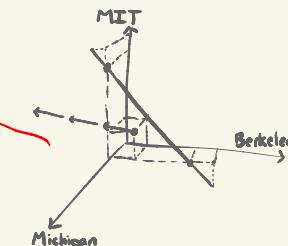
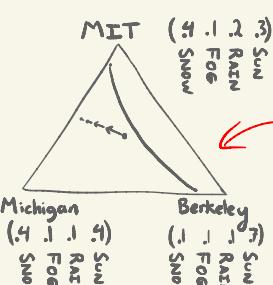
**D. deep architect** SOFTMAX is... a physics-inspired final layer for deep nets



START FOUR SCORE AND ? ?

factory!

**E. researcher** SOFTMAX is... the canonical  $e$ -flat parameterization of the simplex



	MIT	Michigan	Berkeley
MIT	(.33, .33, .33)		
Michigan		(.4, .4, .1)	
Berkeley			(.1, .1, .1)
observe Snow			
	(.13, .13, .03)		
	(.44, .44, .11)		
		(.4, .4, .1)	
observe Snow			
	(.17, .17, .01)		
	(.48, .48, .03)		
		(.4, .4, .1)	
observe Snow			
	(.19, .19, .003)		
	(.46, .46, .008)		