

NEURAL NETWORKS & DEEP LEARNING - (LANCE) ANDREWS AND - WISE 2

BINARY CLASSIFICATION



LOGISTIC REGRESSION

AS A NEURAL NET



THE TASK IS TO LEARN w & b BUT HOW?

1. OPTIMIZE HOW GOOD THE GUESS IS BY MINIMIZING THE DIFF BETWEEN GUESS (\hat{y}) AND TRUTH (y)

$$\text{LOSS} = \mathcal{L}(\hat{y}, y)$$

$$\text{COST} = J(w, b) = \frac{1}{n} \sum_{i=1}^n \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

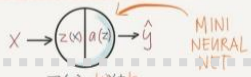
COST = LOSS FOR THE ENTIRE DATASET



FINDING THE MINIMUM WITH GRADIENT DESCENT

- 1. FIND THE DIRECTION (USE DERIVATIVES)
- 2. WALK (UPDATE w & b) AT A α LEARNING RATE
- REPEAT UNTIL YOU REACH BOTTOM (CONVERGE)

PUTTING IT ALL TOGETHER



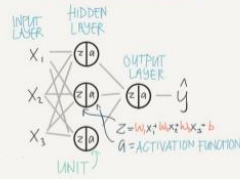
$$z(x) = wx + b$$

$$\hat{y} = a(z) = \sigma(\text{SIGMOID}(z))$$

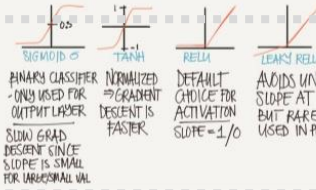
- 1. FORWARD PROPAGATION
- 2. BACKWARD PROPAGATION
- 3. GRADIENT DESCENT
- 4. UPDATE w & b
- REPEAT UNTIL IT CONVERGES

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2 LAYER NEURAL NET



ACTIVATION FUNCTIONS



SIGMOID
BINARY CLASSIFIER - ONLY USED FOR OUTPUT LAYER
SLOW GRAD DESCENT SINCE SLOPE IS SMALL FOR LARGE OR SMALL VAL

TANH
NORMALIZED GRADIENT DESCENT IS FASTER

RELU
DEFAULT CHOICE FOR ACTIVATION SLOPE = 1/0

LEAKY RELU
AVOIDS UNDEF SLOPE AT 0 BUT RARELY USED IN PRACTICE

INITIALIZING W & b

WHAT IF: INIT TO 0
THIS WILL MAKE ALL THE UNITS TO BE THE SAME AND LEARN EXACTLY THE SAME FEATURES
SOLUTION: RANDOM INIT BUT ALSO WANT THEM SMALL SO RAND * 0.01

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SHALLOW NEURAL NETS

WHY ACTIVATION FUNCTIONS?

EX. WITH NO ACTIVATION - $a = z$

$$a^{(1)} = z^{(1)} = w^{(1)}x + b^{(1)} \quad \text{LAYER 1}$$

$$a^{(2)} = z^{(2)} = w^{(2)}a^{(1)} + b^{(2)} \quad \text{LAYER 2}$$

PLUG IN $a^{(1)}$

$$a^{(2)} = w^{(2)}(w^{(1)}x + b^{(1)}) + b^{(2)}$$

$$= w^{(2)}w^{(1)}x + w^{(2)}b^{(1)} + b^{(2)}$$

$$= w^{(2)}w^{(1)}x + b^{(2)}$$

WE COULD JUST AS WELL HAVE SKIPPED THE WHOLE NEURAL NET & USED LIN. REG.

INTRO TO DEEP LEARNING

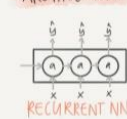
SUPERVISED LEARNING

INPUT: X	OUTPUT: y	NN TYPE
HOME FEATURES	PRICE	STANDARD NN
AD+USER INFO	WILL CLICK ON AD (y/n)	STANDARD NN
IMAGE	OBJECT (1...1000)	CONV. NN (CNN)
AUDIO	TEXT TRANSCRIPT CHINESE	RECURRENT NN (RNN)
ENGLISH	POS OF OTHER CARS	CUSTOM/HYBRID
IMAGE/RADAR		



STANDARD NN
CONVOLUTIONAL NN

NETWORK ARCHITECTURES



RECURRENT NN

NNs CAN DEAL WITH BOTH STRUCTURED & UNSTRUCTURED DATA



STRUCTURED
UNSTRUCTURED
"THE QUICK BROWN FOX"
HUMANS ARE GOOD AT THIS

WHY NOW?



IDEA
EXPERIMENT
CODE
FASTER (COMPUTATION) IS IMPORTANT TO SPEED UP THE ITERATIVE PROCESS

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РИСКИ И СКОРИНГ

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КБ «Ренессанс Кредит»

29 апреля 2020 г.
Москва



Текущая ситуация

1. **Риск не концентрируется** в отдельных сегментах, а растет везде
2. Большая доля вышедших в раннюю просрочку – это **пенсионеры**
3. Растет кол-во обращений клиентов, которые **не могут платить**
4. Более половины из этих клиентов говорят о **снижении дохода** и о **потере работы**



Будущие риски

Кредитные риски – клиенты будут терять работу и доходы и хуже платить по кредитам



Поможет ли скоринг?

1.

СКОРИНГ

=

правила +
модели

2.

**Оперативное
реагирование**

– через
настройку правил

3.

**Источники
данных,**
а не алгоритмы

4.

Базель-II
– модели должны
быть устойчивы к
кризисам

Спасибо за
внимание!

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