자료: 구글 드라이브 (링크는 채팅창)

Machine learning & deep learning basics

Lecture 1

Changho Suh

January 22, 2024

(~1시간)
1교시: logistics
machine learning 기초
① least squares
break
2교시: ② Logistic regression
(~1시간)
③ deep learning
break
3교시: deep learning 훈련방법
(~1시간)

$\boxed{\text{과정개요}}$

- 2주 과정
- ① 제안서 작성
  ② 제안서 작성 위한 이론/실습
- Week 1: 이론/실습
  Week 2: Mini-projects
  제안서 작성법 안내
  제안서 작성 및 발표
- 오전: 이론
  오후: 실습

1. **Logistics**
2. **Machine learning & optimization**

Logistics

Instructor

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2 week course

Week 1: Lecture & Practice session

Week 2: Mini-projects

Proposal

Week 1: Lecture & practice session

1.1: Machine learning & deep learning basics

1.2: Advanced techniques

1.3: Convolutional Neural Network (CNN)

1.4: Recurrent Neural Network (RNN)

1.5: Small data technique: Random Forests

Week 2: Mini-projects & proposal

Group A (권~박한결)

수강생	부서
권태운	전동화시스템시험3팀
김동현	모빌리티컨셉개발팀
김미진	차량제어성능개발팀
김수환	제네시스외장설계팀
김외태	전산재료과학연구팀
김종훈	MSV내구시험팀
김준영	MLV전동화연비시험팀
김진현	제네시스외장설계팀
박정수	자율주행전략기술개발팀
박한결	전동화시스템시험3팀

Group B (박형호~최)

박형호	제네시스샤시설계1팀
신용욱	연구개발품질확보팀
이은주	인포테인먼트기획팀
이창주	전동화시스템시험1팀
임경빈	전자전력제어개발팀
임재영	버추얼이노베이션리서치랩
조대길	자율주행시스템개발팀
조재설	상용제동설계팀
주장규	인포테인먼트기획팀
최정윤	차량에너지제어개발팀

Week 2: Mini-projects & proposal

2.1: Overview of two mini-projects
Mini-project #1

2.2: Mini-project #2
Proposal guideline & sample proposals

2.3: (Group A) Rehearsal & feedback

2.4: (Group B) Rehearsal & feedback

2.5: Proposal presentation

Week 1 schedule

1.1: Machine learning and deep learning basics

Lecture 1: 9:00 am ~ 10:00 am

Lecture 2: 10:10 am ~ 11:10 am

Lecture 3: 11:20 am ~ 12:30 pm

PS 1: 1:30 pm ~ 2:30 pm

PS 2: 2:40 pm ~ 3:40 pm

PS 3: 3:50 pm ~ 5:00 pm

Same format for 1.2 ~ 1.5

15 lectures & 15 PSs

Week 2: Day 1 schedule

2.1: Mini-project overview & mini-project #1

Lecture 16:	9:00 am ~ 10:00 am
Lecture 17:	10:10 am ~ 11:10 am
PS 16:	11:20 am ~ 12:30 pm
PS 17:	1:30 pm ~ 2:30 pm
PS 18:	2:40 pm ~ 3:40 pm
PS 19:	3:50 pm ~ 5:00 pm

Week 2: Day 2 schedule

2.2: Mini-project #2 & proposal guideline

PS 20: 9:00 am ~ 10:00 am

PS 21: 10:10 am ~ 11:10 am

PS 22: 11:20 am ~ 12:30 pm

Lecture 18: 1:30 pm ~ 2:30 pm

Lecture 19: 2:40 pm ~ 3:40 pm

Lecture 20: 3:50 pm ~ 5:00 pm

Week 2: Day 3 schedule

2.3: (Group A) Rehearsal & feedback

09:00 ~ 09:20	권태운
09:20 ~ 09:40	김동현
09:40 ~ 10:00	김미진
10:00 ~ 10:20	김수환
10:20 ~ 10:40	김외태
Break	
10:50 ~ 11:10	김종훈
11:10 ~ 11:30	김준영
11:30 ~ 11:50	김진현
11:50 ~ 12:10	박정수
12:10 ~ 12:30	박한결
Lunch	

13:30 ~ 16:00	Proposal 수정
16:00 ~ 17:00	Q&A

Week 2: Day 4 schedule

2.4: (Group B) Rehearsal & feedback

09:00 ~ 09:20	**박형호**
09:20 ~ 09:40	**신용욱**
09:40 ~ 10:00	**이은주**
10:00 ~ 10:20	**이창주**
10:20 ~ 10:40	**임경빈**
Break	
10:50 ~ 11:10	**임재영**
11:10 ~ 11:30	**조대길**
11:30 ~ 11:50	**조재설**
11:50 ~ 12:10	**주장규**
12:10 ~ 12:30	**최정윤**
Lunch	

13:30 ~ 16:00	**Proposal 수정**
16:00 ~ 17:00	**Q&A**

Week 2: Day 5 schedule

2.5: Proposal presentation

09:00 ~ 09:05	opening
09:05 ~ 09:20	권태운
09:20 ~ 09:35	김동현
09:35 ~ 09:50	김미진
09:50 ~ 10:05	김수환
10:05 ~ 10:20	김외태
10:20 ~ 10:35	김종훈
Break	
10:45 ~ 11:00	김준영
11:00 ~ 11:15	김진현
11:15 ~ 11:30	박정수
11:30 ~ 11:45	박한결
11:45 ~ 12:00	박형호
Lunch	

13:30 ~ 13:45	신용욱
13:45 ~ 14:00	이은주
14:00 ~ 14:15	이창주
14:15 ~ 14:30	임경빈
14:30 ~ 14:45	임재영
Break	
14:45 ~ 15:00	조대길
15:10 ~ 15:25	조재설
15:25 ~ 15:40	주장규
15:40 ~ 15:55	최정윤
Closing	

Reference

1. Lecture Slides (LS)

2. Practice Session (PS):

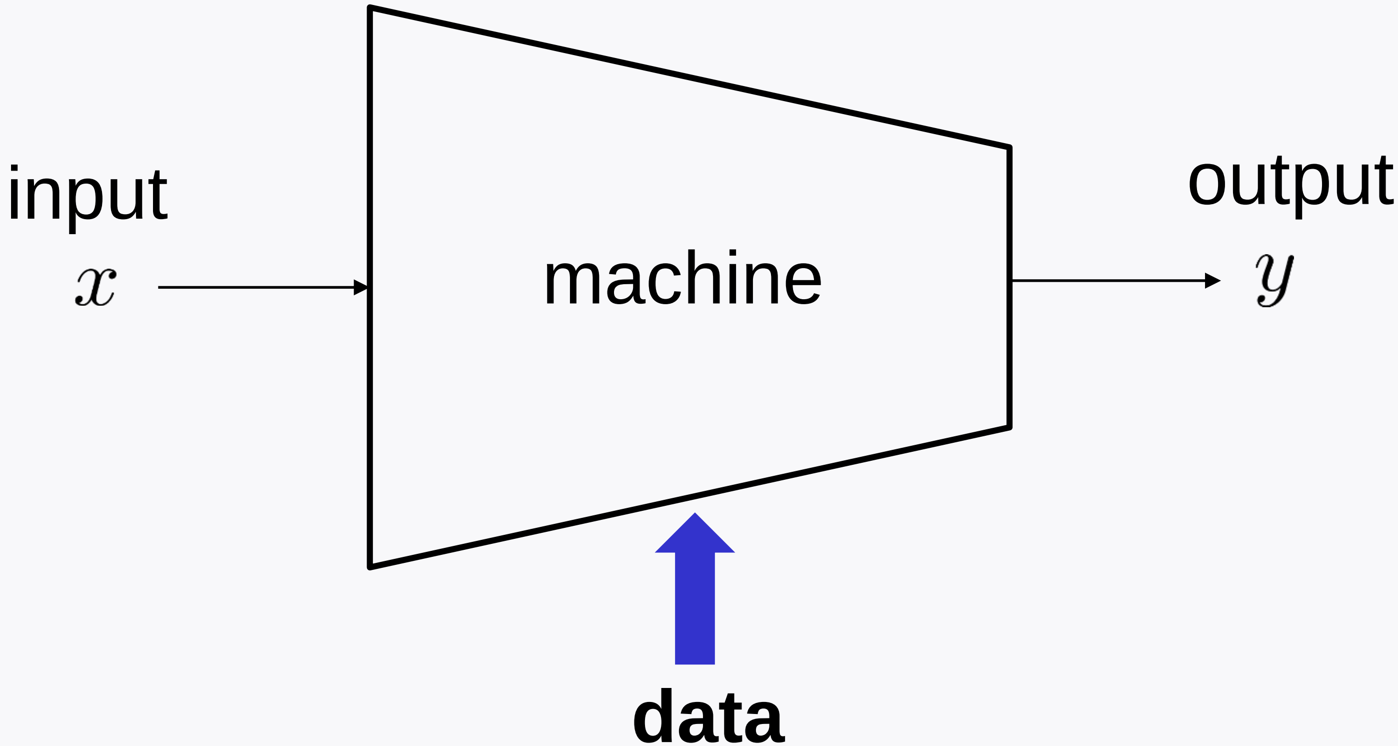
   Slides & python code

All the materials are uploaded in the Google drive:

https://drive.google.com/drive/folders/1PxCsLfZaOiEBoOvIM73JQfD9zUxhb7Dx?usp=drive_link

Machine learning and optimization

Machine learning

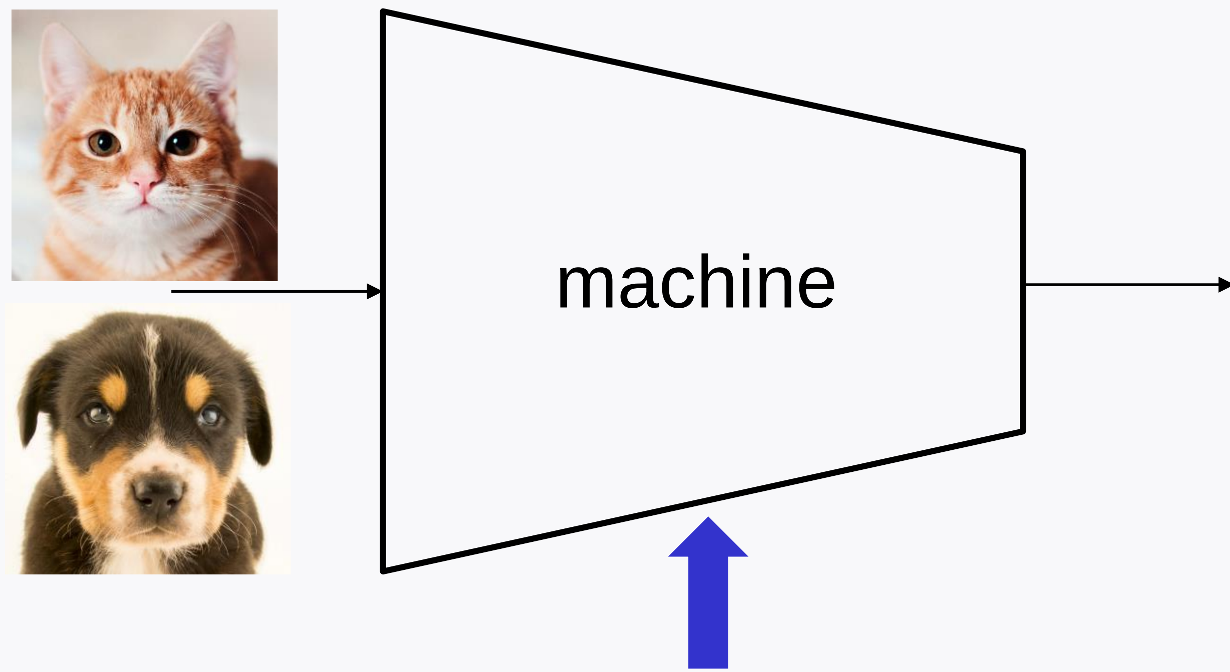


$$\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(m)}, y^{(m)})\}$$

Cat-vs-dog classifier

$x^{(1)} =$

$x^{(2)} =$



$y^{(1)} = 1$

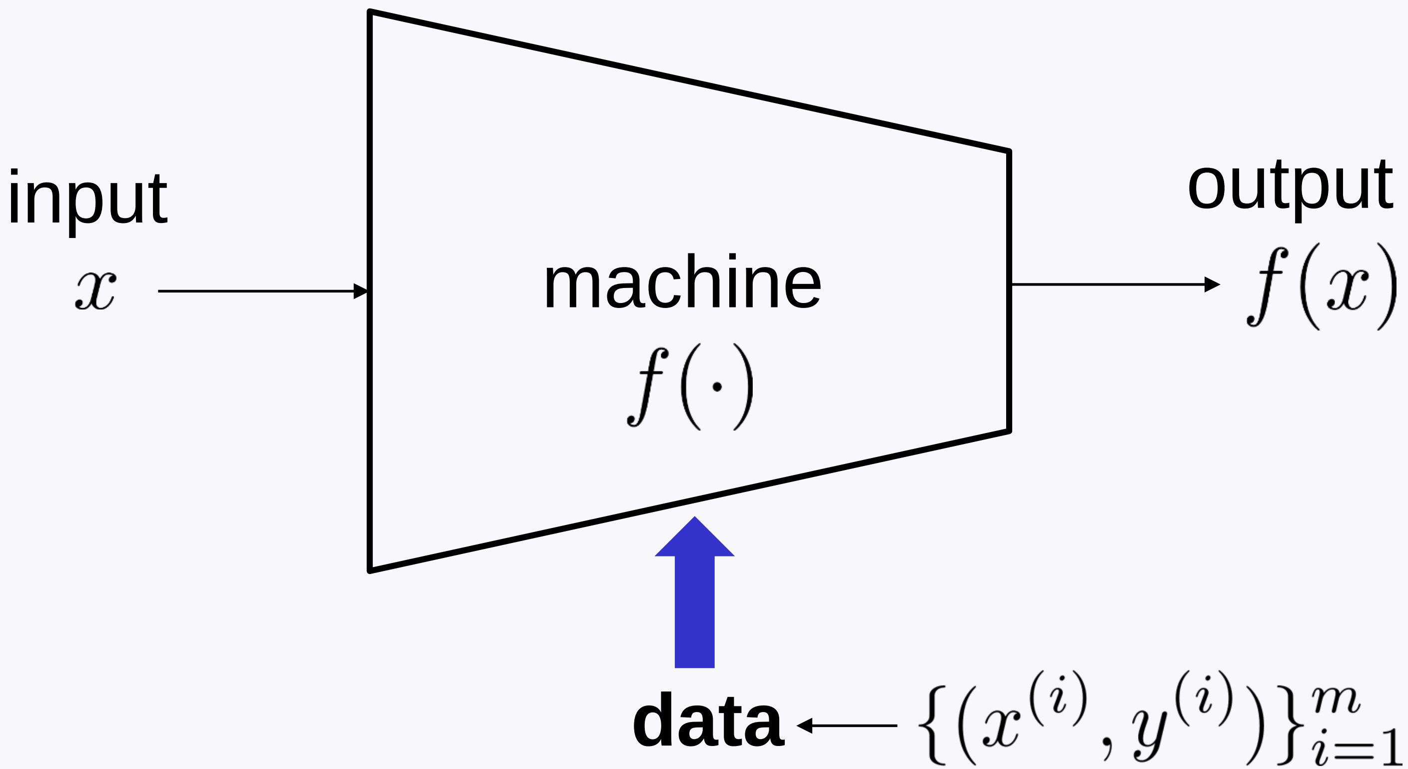
$y^{(2)} = 0$

data

$$\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(m)}, y^{(m)})\}$$

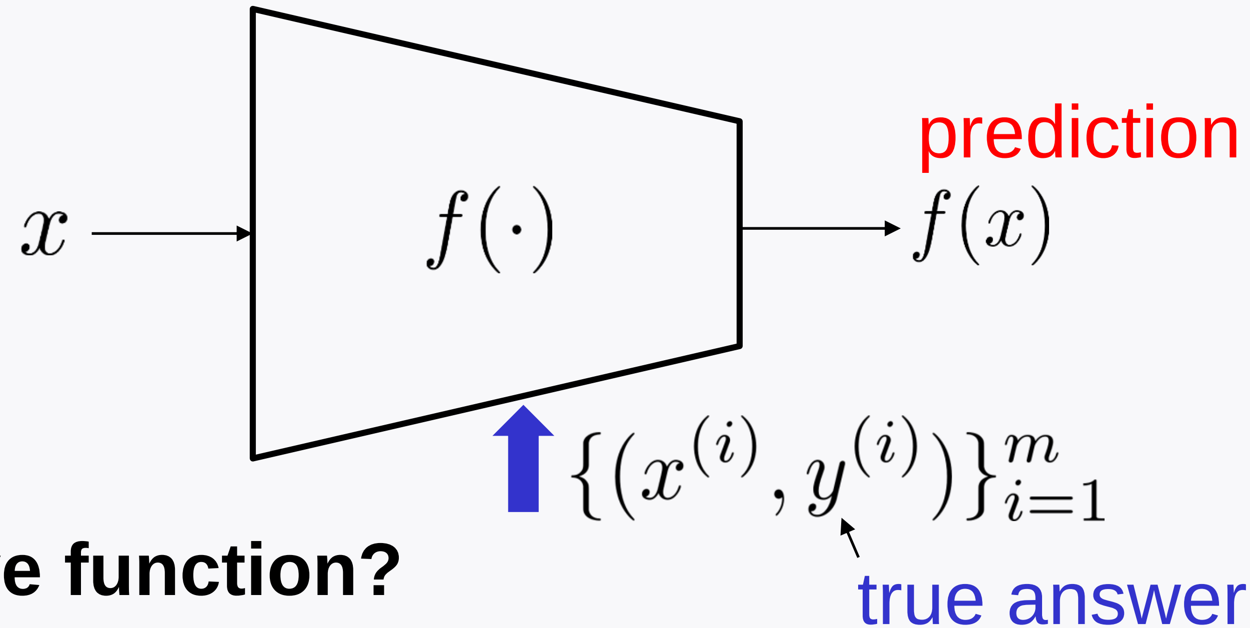
big data → large *m*

Goal of machine learning



Design $f(\cdot)$ using $\{(x^{(i)}, y^{(i)})\}_{i=1}^{m}$

Training via optimization



Objective function?

What we want: $f(x^{(i)}) \approx y^{(i)}$ for all i

prediction true answer

How to **quantify closeness**?

One way is to employ a loss function: $\ell(y^{(i)}, f(x^{(i)}))$

Optimization variable?

$$\min_{f} \sum_{i=1}^{m} \ell(y^{(i)}, f(x^{(i)}))$$

Note: Function optimization

Challenge: There are *so many* choices for function.

How to deal with function optimization?

$$\min_{f_w} \sum_{i=1}^{m} \ell(y^{(i)}, f_w(x^{(i)}))$$

A common way:

Specify a **function class** (e.g., linear, quadratic, …)

Represent $f(\cdot)$ with parameters w

Consider the parameters as optimization variable.

Parameterization

$$\min_{w} \sum_{i=1}^{m} \ell(y^{(i)}, f_{w}(x^{(i)}))$$

Depending on a choice of function class & loss function, there are **three** prominent problems:

1. Least Squares
2. Logistic regression
3. Deep learning

A choice for $f_w(\cdot)$

$$\min_{w} \sum_{i=1}^{m} \ell(y^{(i)}, f_w(x^{(i)}))$$

One architecture was suggested:

Perceptron

Consists of two operations:

1. Inner product: $w^T x$
2. Activation: $f_w(x) = \begin{cases} 1 & \text{if } w^T x > \text{th} \\ 0 & \text{otherwise} \end{cases}$

   (inspired by neuron's behavior)

Frank Rosenblatt '57
(psychologist)

Least Squares

$$\min_{w} \sum_{i=1}^{m} \ell(y^{(i)}, w^T x^{(i)})$$

Employ: Perceptron w/o activation

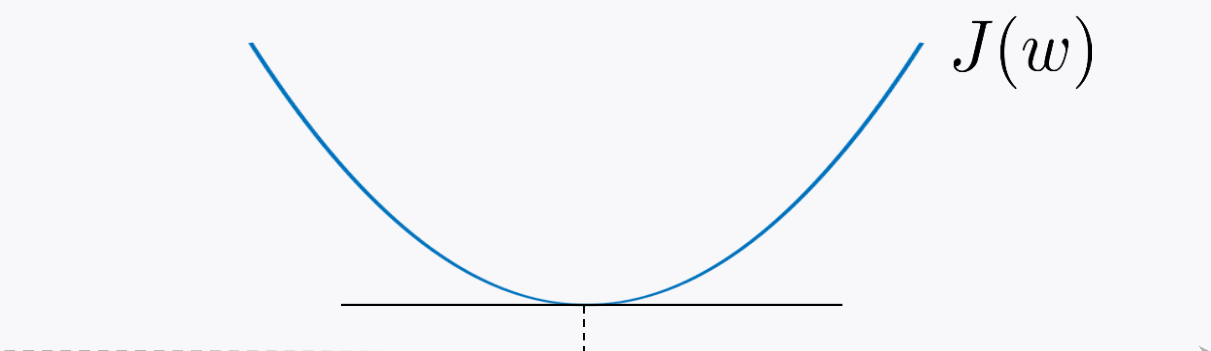
Least Squares

$$\min_{w} \sum_{i=1}^{m} \left\| y^{(i)} - w^T x^{(i)} \right\|^2 =: J(w)$$

Employ: Perceptron w/o activation

A squared error loss: $\ell(y, \hat{y}) = \|y - \hat{y}\|^2$

Convex optimization



w^* closed form solution!

Least Squares

$$\min_{w} \sum_{i=1}^{m} \left\| y^{(i)} - w^T x^{(i)} \right\|^2 =: J(w)$$

Employ: Perceptron w/o activation

A squared error loss: $\ell(y, \hat{y}) = \|y - \hat{y}\|^2$

Convex optimization

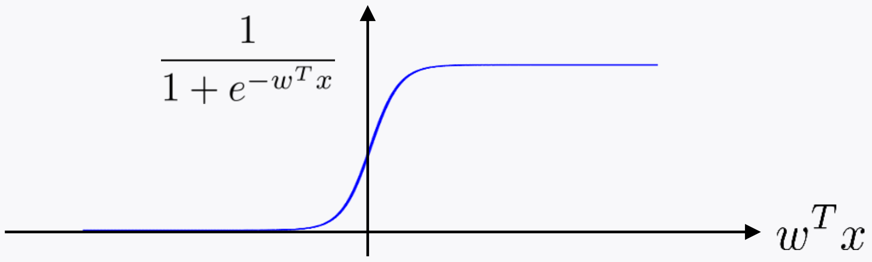
Has the closed form solution.

But performance is not that great.

Logistic regression

$$\min_{w} \sum_{i=1}^{m} \ell\left(y^{(i)}, \frac{1}{1+e^{-w^T x^{(i)}}}\right)$$

Employ: Perceptron w/ logistic function



Cross Entropy (CE) loss:

$$\ell(y,\hat{y}) = -y\log\hat{y} - (1-y)\log(1-\hat{y})$$

Outperforms least squares.

Logistic regression

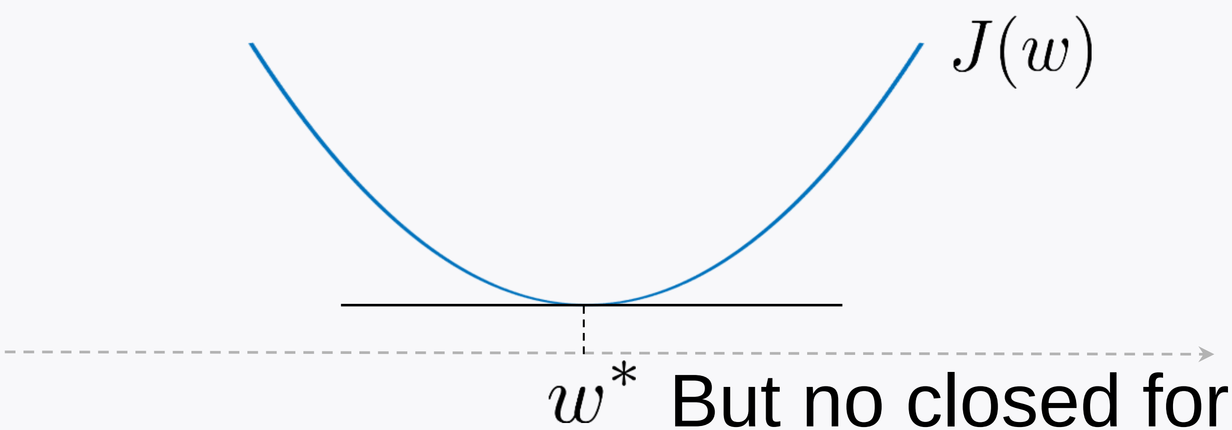
$$\min_w \boxed{\sum_{i=1}^{m} -y^{(i)} \log \frac{1}{1+e^{-w^T x^{(i)}}} - (1-y^{(i)}) \log \left(1 - \frac{1}{1+e^{-w^T x^{(i)}}}\right)}$$

$$=: J(w)$$

Employ: Perceptron w/ logistic function

Cross Entropy (CE) loss

Convex optimization



But no closed form solution

How to train logical regression?

No closed form solution.

Good news: There exist **algorithms** that allow us to find the solution numerically.

One prominent algorithm:

Gradient descent!

Look ahead

Will study: Gradient descent.

Then move onto deep learning.