# **CS70**

# Conditional Expectation and Estimations

#### Kelvin Lee

UC Berkeley

April 20, 2021

Kelvin Lee (UC Berkeley)

Discrete Math and Probability Theory

э April 20, 2021 1/9

-

< (日) × (日) × (1)

Overview



Projection



Orthogonality Property of MMSE



→ Ξ →

・ロト ・ 日 ト ・ 日 ト ・ 日 ト

The Linear Least Squares Estimate (*LLSE*) of Y given X, denoted by L[Y|X] is the linear function a + bX that minimizes

< (日) × (日) × (1)

The Linear Least Squares Estimate (*LLSE*) of Y given X, denoted by L[Y|X] is the linear function a + bX that minimizes

 $\mathbb{E}[(Y-(a+bX))^2].$ 

A (1) > A (2) > A

The Linear Least Squares Estimate (*LLSE*) of Y given X, denoted by L[Y|X] is the linear function a + bX that minimizes

 $\mathbb{E}[(Y-(a+bX))^2].$ 

Theorem

Kelvin Lee (UC Berkeley)

A (1) > A (2) > A

The Linear Least Squares Estimate (*LLSE*) of Y given X, denoted by L[Y|X] is the linear function a + bX that minimizes

$$\mathbb{E}[(Y - (a + bX))^2].$$

Theorem

$$L[Y|X] = a + bX = \mathbb{E}[Y] + \frac{Cov(X, Y)}{Var(X)}(X - \mathbb{E}[X]).$$

< (日) × (日) × (1)

The Linear Least Squares Estimate (*LLSE*) of Y given X, denoted by L[Y|X] is the linear function a + bX that minimizes

$$\mathbb{E}[(Y-(a+bX))^2].$$

#### Theorem

$$L[Y|X] = a + bX = \mathbb{E}[Y] + \frac{Cov(X, Y)}{Var(X)}(X - \mathbb{E}[X]).$$

Proof:

A (1) > A (2) > A

The Linear Least Squares Estimate (*LLSE*) of Y given X, denoted by L[Y|X] is the linear function a + bX that minimizes

$$\mathbb{E}[(Y-(a+bX))^2].$$

Theorem

$$L[Y|X] = a + bX = \mathbb{E}[Y] + \frac{Cov(X, Y)}{Var(X)}(X - \mathbb{E}[X]).$$

Proof:

Expand  $\mathbb{E}[(Y - (a + bX))^2]$  and optimize over a and b.

< □ > < □ > < □ > < □ > < □ > < □ >

The Linear Least Squares Estimate (*LLSE*) of Y given X, denoted by L[Y|X] is the linear function a + bX that minimizes

$$\mathbb{E}[(Y-(a+bX))^2].$$

Theorem

$$L[Y|X] = a + bX = \mathbb{E}[Y] + \frac{Cov(X, Y)}{Var(X)}(X - \mathbb{E}[X]).$$

#### Proof:

Expand  $\mathbb{E}[(Y - (a + bX))^2]$  and optimize over *a* and *b*. Plug in optimal *a*, *b* to a + bX.

#### Projection

<ロト < 四ト < 三ト < 三ト

### Projection

L[Y|X] can be interpreted as the **projection** of Y onto the set of linear functions of X, call it  $\mathcal{L}(X)$ .

A (10) < A (10) </p>

#### Projection

L[Y|X] can be interpreted as the **projection** of Y onto the set of linear functions of X, call it  $\mathcal{L}(X)$ .

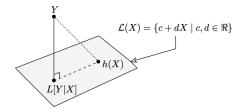


Figure: L[Y|X] is the projection of Y onto  $\mathcal{L}(X)$ .

Kelvin Lee (UC Berkeley)

Discrete Math and Probability Theory

▶ ◀ 볼 ▶ 볼 ∽ ९. April 20, 2021 5/9

イロト イヨト イヨト イヨト

• Two vectors V and W are **orthogonal** to each other if and only if  $\mathbb{E}[VW] = 0.$ 

A D N A B N A B N A B N

- Two vectors V and W are orthogonal to each other if and only if  $\mathbb{E}[VW] = 0.$
- Thus, L[Y|X] = a + bX is the projection of Y onto L(X) if
  Y L[Y|X] is orthogonal to every linear function of X, i.e., if

▲ □ ▶ ▲ □ ▶ ▲ □ ▶

- Two vectors V and W are orthogonal to each other if and only if  $\mathbb{E}[VW] = 0.$
- Thus, L[Y|X] = a + bX is the projection of Y onto L(X) if
  Y L[Y|X] is orthogonal to every linear function of X, i.e., if

$$\forall c, d \in \mathbb{R}, \quad \mathbb{E}[(Y - (a + bX))(c + dX)] = 0.$$

▲ □ ▶ ▲ □ ▶ ▲ □ ▶

- Two vectors V and W are orthogonal to each other if and only if  $\mathbb{E}[VW] = 0.$
- Thus, L[Y|X] = a + bX is the projection of Y onto L(X) if
  Y L[Y|X] is orthogonal to every linear function of X, i.e., if

$$\forall c, d \in \mathbb{R}, \quad \mathbb{E}[(Y - (a + bX))(c + dX)] = 0.$$

Equivalently,

・ 何 ト ・ ヨ ト ・ ヨ ト

- Two vectors V and W are orthogonal to each other if and only if  $\mathbb{E}[VW] = 0.$
- Thus, L[Y|X] = a + bX is the projection of Y onto L(X) if
  Y L[Y|X] is orthogonal to every linear function of X, i.e., if

$$\forall c, d \in \mathbb{R}, \quad \mathbb{E}[(Y - (a + bX))(c + dX)] = 0.$$

Equivalently,

$$\mathbb{E}[Y] = a + b\mathbb{E}[X]$$
 and  $\mathbb{E}[(Y - (a + bX))X] = 0.$ 

・ 何 ト ・ ヨ ト ・ ヨ ト

- Two vectors V and W are orthogonal to each other if and only if  $\mathbb{E}[VW] = 0.$
- Thus, L[Y|X] = a + bX is the projection of Y onto L(X) if
  Y L[Y|X] is orthogonal to every linear function of X, i.e., if

$$\forall c, d \in \mathbb{R}, \quad \mathbb{E}[(Y - (a + bX))(c + dX)] = 0.$$

Equivalently,

$$\mathbb{E}[Y] = a + b\mathbb{E}[X]$$
 and  $\mathbb{E}[(Y - (a + bX))X] = 0.$ 

This is known as the **projection property**.

▲ □ ▶ ▲ □ ▶ ▲ □ ▶

#### **MMSE**

・ロト ・ 日 ト ・ 日 ト ・ 日 ト

The *MMSE* of Y given X is given by 𝔼[Y|X], which is the conditional expectation of Y given X.

(日)



- The *MMSE* of Y given X is given by 𝔼[Y|X], which is the conditional expectation of Y given X.
- The conditional expectation of Y given X is defined by

< (日) × (日) × (1)

- The *MMSE* of Y given X is given by 𝔼[Y|X], which is the conditional expectation of Y given X.
- The conditional expectation of Y given X is defined by

$$\mathbb{E}[Y|X=x] = \sum_{y} y \cdot \mathbb{P}(Y=y|X=x) = \sum_{y} y \cdot \frac{\mathbb{P}(X=x,Y=y)}{\mathbb{P}(X=x)}.$$

< (日) × (日) × (1)

Kelvin Lee (UC Berkeley)

Discrete Math and Probability Theory

▶ ◀ 볼 ▶ 볼 ∽ ९. April 20, 2021 7/9

A D N A B N A B N A B N

Lemma (Orthogonality Property of MMSE)

For any function  $\phi(\cdot)$ , one has

< □ > < 同 > < 回 > < 回 > < 回 >

Lemma (Orthogonality Property of *MMSE*) For any function  $\phi(\cdot)$ , one has

 $\mathbb{E}[(Y - \mathbb{E}[Y|X])\phi(X)] = 0.$ 

< □ > < □ > < □ > < □ > < □ > < □ >

Lemma (Orthogonality Property of *MMSE*) For any function  $\phi(\cdot)$ , one has

 $\mathbb{E}[(Y - \mathbb{E}[Y|X])\phi(X)] = 0.$ 

Moreover, if the function g(X) is such that

- 4 回 ト 4 ヨ ト 4 ヨ ト

Lemma (Orthogonality Property of *MMSE*) For any function  $\phi(\cdot)$ , one has

 $\mathbb{E}[(Y - \mathbb{E}[Y|X])\phi(X)] = 0.$ 

Moreover, if the function g(X) is such that

 $\forall \phi(\cdot), \quad \mathbb{E}[(Y - g(X))\phi(X)] = 0,$ 

< □ > < □ > < □ > < □ > < □ > < □ >

Lemma (Orthogonality Property of *MMSE*) For any function  $\phi(\cdot)$ , one has

 $\mathbb{E}[(Y - \mathbb{E}[Y|X])\phi(X)] = 0.$ 

Moreover, if the function g(X) is such that

$$\forall \phi(\cdot), \quad \mathbb{E}[(Y - g(X))\phi(X)] = 0,$$

then  $g(X) = \mathbb{E}[Y|X]$ .

< □ > < □ > < □ > < □ > < □ > < □ >

Kelvin Lee (UC Berkeley)

Discrete Math and Probability Theory

▶ ▲ ≣ ▶ ≣ ∽ ९ ୯ April 20, 2021 8/9

Image: A match a ma

• Linearity:

Kelvin Lee (UC Berkeley)

(日)

• Linearity:

$$\mathbb{E}[a_1Y_1 + a_2Y_2 \mid X] = a_1\mathbb{E}[Y_1|X] + a_2\mathbb{E}[Y_2|X];$$

(日)

• Linearity:

$$\mathbb{E}[a_1Y_1+a_2Y_2\mid X]=a_1\mathbb{E}[Y_1\mid X]+a_2\mathbb{E}[Y_2\mid X];$$

• Factoring known values:

→ < Ξ →</p>

• Linearity:

$$\mathbb{E}[a_1Y_1+a_2Y_2\mid X]=a_1\mathbb{E}[Y_1\mid X]+a_2\mathbb{E}[Y_2\mid X];$$

• Factoring known values:

$$\mathbb{E}[h(X)Y \mid X] = h(X)\mathbb{E}[Y|X];$$

→ < Ξ →</p>

• Linearity:

$$\mathbb{E}[a_1Y_1 + a_2Y_2 \mid X] = a_1\mathbb{E}[Y_1|X] + a_2\mathbb{E}[Y_2|X];$$

• Factoring known values:

$$\mathbb{E}[h(X)Y \mid X] = h(X)\mathbb{E}[Y|X];$$

• Law of iterated expectation:

< ⊒ >

• Linearity:

$$\mathbb{E}[a_1Y_1+a_2Y_2\mid X]=a_1\mathbb{E}[Y_1\mid X]+a_2\mathbb{E}[Y_2\mid X];$$

• Factoring known values:

$$\mathbb{E}[h(X)Y \mid X] = h(X)\mathbb{E}[Y|X];$$

• Law of iterated expectation:

$$\mathbb{E}[\mathbb{E}[Y|X]] = \mathbb{E}[Y].$$

- 3 ► ►

• Linearity:

$$\mathbb{E}[a_1Y_1 + a_2Y_2 \mid X] = a_1\mathbb{E}[Y_1|X] + a_2\mathbb{E}[Y_2|X];$$

• Factoring known values:

$$\mathbb{E}[h(X)Y \mid X] = h(X)\mathbb{E}[Y|X];$$

• Law of iterated expectation:

$$\mathbb{E}[\mathbb{E}[Y|X]] = \mathbb{E}[Y].$$

• Independence:

< ∃ ►

• Linearity:

$$\mathbb{E}[a_1Y_1 + a_2Y_2 \mid X] = a_1\mathbb{E}[Y_1|X] + a_2\mathbb{E}[Y_2|X];$$

• Factoring known values:

$$\mathbb{E}[h(X)Y \mid X] = h(X)\mathbb{E}[Y|X];$$

• Law of iterated expectation:

$$\mathbb{E}[\mathbb{E}[Y|X]] = \mathbb{E}[Y].$$

• Independence:

$$\mathbb{E}[Y|X] = \mathbb{E}[Y].$$

Kelvin Lee (UC Berkeley)

Discrete Math and Probability Theory

< ∃ ►

# **Problem Time!**

Kelvin Lee (UC Berkeley)

Discrete Math and Probability Theory

▶ < ≣ ▶ ≣ ∽ ९ . April 20, 2021 9/9

A D N A B N A B N A B N