# ACTEX Learning Flashcards 

Learning \& Memorizing Key Topics and Formulas

# SOA Exam SRM Spring 2019 Edition 

Runhuan Feng, Ph.D., FSA, CERA, Daniël Linders, Ph.D. Ambrose Lo, Ph.D., FSA, CERA

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## Dreface

This set of flashcards is meant to complement the ACTEX Study Manual for SOA Exam SRM (Statistics for Risk Modeling). Fully revised in response to the May 2019 edition of the SRM study manual, these flashcards provide a concise summary of the SRM exam material in a readable and presentationoriented format with a view to maximizing retention. Important formulas are displayed to facilitate identification and memorization. Suggestions are given as to which formulas, in our opinion, must be memorized, which formulas are important but can be easily deduced from other results, and which formulas are of secondary importance. The flashcards are particularly suitable for last-minute review-don't forget to take them with you on your way to the CBT exam center!

It should be noted, however, that these flashcards add value to, but are no substitute for reading the SRM study manual. Examples and problems, which are key to exam success, are not included or discussed in these flashcards. We suggest that you first read the manual carefully, go over the
in-text examples and (most of the) end-of-chapter problems, then use the flashcards as a means to review what you have learned and to ensure that you have mastered all of the key concepts.

As with the SRM study manual, we would be extremely grateful if you could share your comments and suggestions on these flashcards with us and bring to our attention any potential errors. Please direct your comments and questions to ambrose-lo@uiowa.edu. The authors will try their best to respond to any inquiries as soon as possible and an ongoing list of updates will be maintained online at https://sites.google.com/site/ ambroseloyp/publications/SRM

We wish you the best of luck with your SRM exam!

Runhuan Feng Daniël Linders Ambrose Lo February 2019

## Part I

## Regression Models

## Chapter 1

## Simple Linear Regression

### 1.1 Basics

- Simple linear regression (SLR) model equation: An approximately linear relationship between $y$ and $x$ :

$$
\underbrace{y}_{\text {response }}=\underbrace{\beta_{0}+\beta_{1} x}_{\text {regression function }}+\underbrace{\varepsilon}_{\text {error }}
$$

where
$y$ is the response variable (a.k.a. dependent variable),
$x$ is the explanatory variable (a.k.a. predictors, features),
$\beta_{0}$ (intercept) and $\beta_{1}$ (slope) are regression coefficients,
$\varepsilon$ is the random error term.
In the above model, we say that $y$ is regressed on $x$ (denoted $y \sim x)$.

- Defining property of SLR: There is only one explanatory variable, namely, $x$.
- Model assumptions:

A1. The $y_{i}$ 's are realizations of random variables, while the $x_{i}$ 's are nonrandom.

A2. $\varepsilon_{1}, \varepsilon_{2}, \ldots, \varepsilon_{n}$ are independent with

$$
\mathbb{E}\left[\varepsilon_{i}\right]=0 \quad \text { and } \quad \operatorname{Var}\left(\varepsilon_{i}\right)=\sigma^{2}
$$

for all $i=1,2, \ldots, n$.
Almost always further assume that $\varepsilon_{i}$ 's are normally distributed, i.e.,

$$
\varepsilon_{i} \stackrel{\text { i.i.d. }}{\sim} \mathrm{N}\left(0, \sigma^{2}\right)
$$

### 1.2 Model Fitting by Least Squares Method

- Idea of least squares method: Choose $\beta_{0}$ and $\beta_{1}$ to make the sum of squares

$$
\operatorname{SS}\left(\beta_{0}, \beta_{1}\right):=\sum_{i=1}^{n}[\underbrace{y_{i}}_{\text {obs. value }}-(\underbrace{\beta_{0}+\beta_{1} x_{i}}_{\text {candidate fitted value }})]^{2}
$$

the "least."

- Least squares estimates (LSEs):

$$
\hat{\beta}_{1}=\frac{S_{x y}}{S_{x x}}=\frac{\sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)\left(y_{i}-\bar{y}\right)}{\sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)^{2}} \quad \text { and } \quad \hat{\beta}_{0}=\bar{y}-\hat{\beta}_{1} \bar{x},
$$

where

$$
\begin{aligned}
& \triangleright S_{x y}:=\sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)\left(y_{i}-\bar{y}\right)=\sum_{i=1}^{n} x_{i} y_{i}-n \bar{x} \bar{y} \\
& \triangleright S_{x x}:=\sum_{i=1}^{n}\left(x_{i}-\bar{x}\right)^{2}=\sum_{i=1}^{n} x_{i}^{2}-n \bar{x}^{2}
\end{aligned}
$$

(Suggestion: Remember the formulas for $\hat{\beta}_{0}$ and $\hat{\beta}_{1}$ !)

- How can the calculation of LSEs be tested?

Case 1. Given the raw data $\left\{\left(x_{i}, y_{i}\right)\right\}_{i=1}^{n}$ with a relatively small $n$ (e.g., $n \leq 10$ )

Enter the data into your financial calculator and read the output from its statistics functions.
Case 2. Given summarized data in the form of various sums, e.g.,

$$
\sum_{i=1}^{n} x_{i}, \quad \sum_{i=1}^{n} y_{i}, \quad \sum_{i=1}^{n} x_{i}^{2}, \quad \sum_{i=1}^{n} y_{i}^{2}, \quad \sum_{i=1}^{n} x_{i} y_{i} .
$$

Expand the products in the two sums that appear in $\hat{\beta}_{1}$ and use the alternative form

$$
\hat{\beta}_{1}=\frac{\sum_{i=1}^{n} x_{i} y_{i}-n \bar{x} \bar{y}}{\sum_{i=1}^{n} x_{i}^{2}-n \bar{x}^{2}}
$$

- An alternative formula for $\hat{\boldsymbol{\beta}}_{1}$ in terms of sample correlation:

$$
\hat{\beta}_{1}=r \times \frac{s_{y}}{s_{x}}, \quad\left(\text { Warning: Not } r \times \frac{s_{x}}{s_{y}}!\right)
$$

where
$\triangleright s_{x}$ and $s_{y}$ are the sample standard deviations of $x$ and $y$
$\triangleright r$ is the sample correlation coefficient between $x$ and $y$

- Application of this formula: Slope estimates when regressing $y$ on $x$ and regressing $x$ on $y$ are related via

$$
\hat{\beta}_{1}^{y \sim x} \times \hat{\beta}_{1}^{x \sim y}=\underbrace{r^{2}=R^{2}}_{\text {see Sect. } 1.3}
$$

- Fitted values and residuals: Given $\hat{\beta}_{0}$ and $\hat{\beta}_{1}$, we can compute:

1. The fitted value (a.k.a. predicted value) $\hat{y}_{i}=\hat{\beta}_{0}+\hat{\beta}_{1} x_{i}$
$\triangleright$ Mnemonic: Obtained from the model equation by

$$
\beta_{0} \rightarrow \hat{\beta}_{0}, \quad \beta_{1} \rightarrow \hat{\beta}_{1}, \quad \varepsilon_{i} \rightarrow 0
$$

$\triangleright$ Ideally, $\hat{y}_{i}$ should be close to $y_{i}$.
2. The residual $e_{i}=y_{i}-\hat{y}_{i}$
$\triangleright$ Memory alert: Not $\hat{y}_{i}-y_{i}$ !
$\triangleright$ Completely different from $\varepsilon_{i}$, which is unobservable and which $e_{i}$ serves to approximate.

- Graphical illustration of fitted regression line and definitions of fitted value and residual:

- Sum-to-zero constraints on residuals:

1. $\sum_{i=1}^{n} e_{i}=0$, provided that $\beta_{0}$ is included in the model Meaning: The residuals offset one another to produce a zero sum; they are negatively correlated.
2. $\sum_{i=1}^{n} x_{i} e_{i}=0$

Meaning: The residuals and the explanatory variable values are uncorrelated.

Mnemonic: $\hat{\beta}_{0}$ and $\hat{\beta}_{1}$ satisfy

$$
\begin{aligned}
\frac{\partial}{\partial \beta_{0}} \operatorname{SS}\left(\hat{\beta}_{0}, \hat{\beta}_{1}\right) & =-2 \sum_{i=1}^{n}[\overbrace{y_{i}-\left(\hat{\beta}_{0}+\hat{\beta}_{1} x_{i}\right)}^{e_{i}}]=0 \\
\frac{\partial}{\partial \beta_{1}} \operatorname{SS}\left(\hat{\beta}_{0}, \hat{\beta}_{1}\right) & =-2 \sum_{i=1}^{n} x_{i}[\underbrace{y_{i}-\left(\hat{\beta}_{0}+\hat{\beta}_{1} x_{i}\right)}_{e_{i}}]=0
\end{aligned}
$$

### 1.3 Assessing Goodness of Fit of the Model

- Three kinds of sums of squares:

| Sum of <br> Squares | Abbrev. | Def. | What Does It Measure? |
| :---: | :---: | :--- | :--- |
| Total SS | TSS | Variation of <br> response values <br> about $\bar{y}$ | Amount of variability inher- <br> ent in the response prior to <br> performing regression |
| Residual SS <br> or | RSS | Variation of <br> response values <br> about fitted <br> regression line | • Goodness of fit of the SLR <br> model (the lower, the better) <br> • Amount of variability of <br> response left unexplained <br> even after introduction of $x$ |
| Regression SS | Reg SS | Variation <br> explained by SLR <br> (or the knowledge <br> of $x)$ | How effective SLR model is <br> in explaining the variation in <br> $y$ |

- ANOVA identity:

$$
\underbrace{\sum_{i=1}^{n}\left(y_{i}-\bar{y}\right)^{2}}_{\text {TSS }}=\underbrace{\sum_{i=1}^{n}\left(y_{i}-\hat{y}_{i}\right)^{2}}_{\text {RSS }}+\underbrace{\sum_{i=1}^{n}\left(\hat{y}_{i}-\bar{y}\right)^{2}}_{\text {Reg SS }}
$$

- Coefficient of determination:
$\triangleright$ Definition: $R^{2}=\frac{\operatorname{Reg} \mathrm{SS}}{\mathrm{TSS}}=1-\frac{\mathrm{RSS}}{\mathrm{TSS}}$
$\triangleright$ Measures the proportion of variation of response (about its mean) explained by the SLR model
$\triangleright$ The higher, the better
- Specialized formulas for Reg SS and $R^{2}$ under SLR:
$\triangleright \operatorname{Reg} \mathrm{SS}=\hat{\beta}_{1}^{2} S_{x x}$
$\triangleright R^{2}=r^{2}=\operatorname{Corr}(x, y)^{2}$ (square of correlation between $x$ and $y$ )


## - ANOVA table:

| Source | Sum of Squares | $d f$ | Mean Square | $F$-value |
| :--- | :--- | :---: | :--- | :---: |
| Regression | Reg SS | 1 | Reg SS $/ 1$ | $?$ |
| Error | RSS | $n-2$ | $s^{2}=\operatorname{RSS} /(n-2)$ |  |
| Total | TSS | $n-1$ |  |  |

Structure:
$\triangleright$ Different sources of variation in $y$
$\triangleright$ Some "informal" rules for counting $d f$ :

- Reg SS has $1 d f$ because of one explanatory variable
- RSS has $2 d f$ subtracted from $n$ because of two parameters, $\beta_{0}$ and $\beta_{1}$
$\triangleright$ Dividing an SS by its $d f$ results in a mean square (MS).
- Mean square error:

$$
s^{2}=\frac{\mathrm{RSS}}{\mathrm{df} \text { of RSS }}=\frac{\sum_{i=1}^{n} e_{i}^{2}}{n-2} ;
$$

$s=\sqrt{s^{2}}$ is the residual standard deviation or residual standard error.

- $\boldsymbol{F}$-test:
$\triangleright$ Hypotheses:

$$
\underbrace{\mathrm{H}_{0}: \beta_{1}=0}_{\text {i.i.d. model }} \text { vs. } \underbrace{\mathrm{H}_{a}: \beta_{1} \neq 0}_{\text {SLR model }} ;
$$

a test of the significance/usefulness of $x$ in explaining $y$
$\triangleright F$-statistic:

$$
F=\frac{\operatorname{Reg} \mathrm{SS} /(\mathrm{df} \text { of } \operatorname{Reg} \mathrm{SS})}{\mathrm{RSS} /(\mathrm{df} \text { of } \mathrm{RSS})}=\frac{\operatorname{Reg} \mathrm{SS} / 1}{\mathrm{RSS} /(n-2)}
$$

$\triangleright$ Behavior of $F$-statistic:

- $\mathrm{H}_{0}$ : Expected value close to one
$-\mathrm{H}_{a}$ : Tends to be large
- F-test: (Cont.)
$\triangleright$ Going between $F$-statistic and $R^{2}$ :

$$
F=(n-2)\left(\frac{\mathrm{Reg} \mathrm{SS} / \mathrm{TSS}}{\mathrm{RSS} / \mathrm{TSS}}\right)=(n-2)\left(\frac{R^{2}}{1-R^{2}}\right)
$$

(Mnemonic: Divide both the numerator and denominator of the $F$ statistic by TSS to get $R^{2}$.)

### 1.4 Statistical Inference about $\beta_{0}$ and $\beta_{1}$

- Sampling distributions of $\hat{\beta}_{0}$ and $\hat{\beta}_{1}$ :
- Linear combination formulas:

$$
\begin{array}{ll}
\hat{\beta}_{1}=\sum_{i=1}^{n} w_{i} y_{i}, & \text { where } w_{i}=\frac{x_{i}-\bar{x}}{S_{x x}} \\
\hat{\beta}_{0}=\sum_{i=1}^{n} w_{i, 0} y_{i}, & \text { where } w_{i, 0}=\frac{1}{n}-\bar{x} w_{i}
\end{array}
$$

(Suggestion: Remembering these weights is recommended, but not absolutely essential)

- Sampling distributions of $\hat{\beta}_{0}$ and $\hat{\beta}_{1}$ : (Cont.)
$\triangleright$ Unbiased: $\mathbb{E}\left[\hat{\beta}_{j}\right]=\beta_{j}$ for $j=0,1$
- Variances:

$$
\operatorname{Var}\left(\hat{\beta}_{0}\right)=\sigma^{2}\left(\frac{1}{n}+\frac{\bar{x}^{2}}{S_{x x}}\right) \quad \text { and } \quad \operatorname{Var}\left(\hat{\beta}_{1}\right)=\frac{\sigma^{2}}{S_{x x}}
$$

(Suggestion: Remember these two formulas!)
$\triangleright$ Estimated variances: With $\sigma^{2} \rightarrow s^{2}(\mathrm{MSE})$,

$$
\widehat{\operatorname{Var}}\left(\hat{\beta}_{0}\right)=s^{2}\left(\frac{1}{n}+\frac{\bar{x}^{2}}{S_{x x}}\right) \quad \text { and } \quad \widehat{\operatorname{Var}}\left(\hat{\beta}_{1}\right)=\frac{s^{2}}{S_{x x}}
$$

- $t$-test:

$$
\beta_{j} \neq d
$$

$\triangleright$ Hypotheses: $\mathrm{H}_{0}: \beta_{j}=d$ vs. $\mathrm{H}_{a}: \beta_{j}>d$

$$
\beta_{j}<d
$$

$\triangleright$ Important special case: $d=0$ (i.e., to test if $x$ is useful)
$\triangleright t$-statistic:

$$
t\left(\hat{\beta}_{j}\right)=\frac{\text { LSE }- \text { hypothesized value }}{\text { standard error of LSE }}=\frac{\hat{\beta}_{j}-d}{\mathrm{SE}\left(\hat{\beta}_{j}\right)}
$$

$\triangleright$ Null distribution: $t\left(\hat{\beta}_{j}\right) \stackrel{\mathrm{H}_{0}}{\sim} t_{n-2}$
$\triangleright$ Decision rules and $p$-value:

| $\mathrm{H}_{a}$ | Decision Rule | $p$-value $\left(t\right.$ is the observed value of $\left.t\left(\hat{\beta}_{j}\right)\right)$ |
| :---: | :--- | :--- |
| $\beta_{j} \neq d$ | $\left\|t\left(\hat{\beta}_{j}\right)\right\|>t_{n-2, \alpha / 2}$ | $\mathbb{P}\left(\left\|t_{n-2}\right\|>\|t\|\right)=2 \mathbb{P}\left(t_{n-2}>\|t\|\right)$ |
| $\beta_{j}>d$ | $t\left(\hat{\beta}_{j}\right)>t_{n-2, \alpha}$ | $\mathbb{P}\left(t_{n-2}>t\right)$ |
| $\beta_{j}<d$ | $t\left(\hat{\beta}_{j}\right)<-t_{n-2, \alpha}$ | $\mathbb{P}\left(t_{n-2}<t\right)$ |

- Confidence intervals (CIs) for $\beta_{0}$ and $\beta_{1}$ : General structure is
$\mathrm{LSE} \pm t$-quantile $\times$ Standard error $=\hat{\beta}_{j} \pm t_{n-2, \alpha / 2} \times \operatorname{SE}\left(\hat{\beta}_{j}\right)$.
$\triangleright$ E.g.: $\hat{\beta}_{1} \pm t_{n-2, \alpha / 2} \times \operatorname{SE}\left(\hat{\beta}_{1}\right)$ is the CI for $\beta_{1}$
$\triangleright$ Construction requires formulas of $\operatorname{SE}\left(\hat{\beta}_{0}\right)$ and $\operatorname{SE}\left(\hat{\beta}_{1}\right)$
- Relationship between $\boldsymbol{F}$-test and $\boldsymbol{t}$-test for $\mathrm{H}_{0}: \beta_{1}=0$ :
$\triangleright$ Direct connection between test statistics:

$$
F=t\left(\hat{\beta}_{1}\right)^{2}
$$

$\triangleright$ Importance: Connect information about $\hat{\beta}_{1}$ (captured by $t\left(\hat{\beta}_{1}\right)$ ) with information about the whole model (captured by $F$ )

### 1.5 Prediction

- Target (random variable):

$$
y_{*}=\beta_{0}+\beta_{1} x_{*}+\varepsilon_{*},
$$

where $x_{*}$ is explanatory variable value of interest

- Generic setting:

| response | known values of explanatory variables |
| :---: | :--- |
| $\underline{y}$ | $\underline{x}$ |
| observed | $y_{1}$ |


| Unobserved <br> (future) data | $y_{*}$ (target) |
| :--- | :--- |$\leftarrow$| $x_{*}$ |
| :--- |

- Point predictor:

$$
\hat{y}_{*}=\hat{\beta}_{0}+\hat{\beta}_{1} x_{*}
$$

(Mnemonic: Set $\beta_{0} \rightarrow \hat{\beta}_{0}, \beta_{1} \rightarrow \hat{\beta}_{1}$, and $\varepsilon_{*} \rightarrow 0$; same trick as fitted values)

- $100(1-\alpha) \%$ prediction interval:

$$
\begin{aligned}
& \text { point predictor } \pm t \text {-quantile } \times \text { st. error of prediction error } \\
= & \hat{y}_{*} \pm t_{n-2, \alpha / 2} \times \mathrm{SE}\left(y_{*}-\hat{y}_{*}\right) \\
= & \left(\hat{\beta}_{0}+\hat{\beta}_{1} x_{*}\right) \pm t_{n-2, \alpha / 2} \sqrt{s^{2}\left[1+\frac{1}{n}+\frac{\left(x_{*}-\bar{x}\right)^{2}}{S_{x x}}\right]}
\end{aligned}
$$

(Suggestion: Remember this formula!)

- Remarks on the structure of the prediction interval: Two sources of uncertainty associated with prediction:

$$
\widehat{\operatorname{Var}}\left(y_{*}-\hat{y}_{*}\right)=\underbrace{s^{2}}_{(1)}+\underbrace{s^{2}\left[\frac{1}{n}+\frac{\left(x_{*}-\bar{x}\right)^{2}}{S_{x x}}\right]}_{(2)}
$$

(1) Variability of the random error $\varepsilon_{*}$ : Reflected in the extra $s^{2}$
(2) Estimation of the true regression line at $x_{*}$ :
$\triangleright \hat{\beta}_{0}$ and $\hat{\beta}_{1}$ are only estimates of $\beta_{0}$ and $\beta_{1}$, and are subject to sampling fluctuations
$\triangleright$ Variance of prediction error minimized when $x_{*}=\bar{x}$ and increases quadratically as $x_{*}$ moves away from $\bar{x}$

