Summary of Topics for the Final Exam
STA 371G, Spring 2014

Listed below are the major topics covered in class that are likely to be in the Final Exam. Good Luck!

- Mean (expectation), variance and standard deviation of a random variable.

$$\mathbb{E}[X] = \sum_{i=1}^{n} x_i P(X = x_i), \quad \mathrm{Var}[X] = \sum_{i=1}^{n} (x_i - \mathbb{E}[X])^2 P(X = x_i), \quad \mathrm{sd}[X] = \sqrt{\mathrm{Var}[X]}$$

- Add a constant to a random variable, multiply a random variable by a constant.
  If $Y = a + bX$, then

$$\mathbb{E}[Y] = a + b\mathbb{E}[X], \quad \mathrm{Var}[Y] = b^2 \mathrm{Var}[X], \quad \mathrm{sd}[Y] = |b| \times \mathrm{sd}[X].$$

- Conditional, joint and marginal probabilities.

$$P(Y = y|X = x) = \frac{P(Y = y, X = x)}{P(X = x)}$$

$$P(Y = y, X = x) = P(Y = y|X = x)P(X = x)$$

$$P(Y = y) = \sum_{x} P(Y = y, X = x)$$

- Independent random variables, sum of independent random variables.
  - Two random variables X and Y are independent if $P(Y = y|X = x) = P(Y = y)$ for all possible x and y.
  - If X and Y are independent , then $P(Y = y, X = x) = P(Y = y)P(X = x)$.
  - If $Y = a_0 + a_1 X_1 + a_2 X_2 + \cdots + a_n X_n$, then

    $$\mathbb{E}[Y] = a_0 + a_1 \mathbb{E}[X_1] + a_2 \mathbb{E}[X_2] + \cdots + a_n \mathbb{E}[X_n].$$

    If X_i and X_j are independent for $i \neq j$, then we further have

    $$\mathrm{Var}[Y] = a_1^2 \mathrm{Var}[X_1] + a_2^2 \mathrm{Var}[X_2] + \cdots + a_n^2 \mathrm{Var}[X_n].$$

- Normal distribution $X \sim \mathcal{N}(\mu, \sigma^2)$, where μ is the mean, σ^2 is the variance, and σ is the standard deviation.
  - Probability density function: area under the curve represents probability.
  - Standard normal distribution $Z \sim \mathcal{N}(0, 1)$.
  - Standardizing a normal random variable $Z = \frac{X-\mu}{\sigma} \sim \mathcal{N}(0, 1)$.
  - $P(X < x) = P(\frac{X-\mu}{\sigma} < \frac{x-\mu}{\sigma}) = P(Z < \frac{x-\mu}{\sigma})$.

- $P(-1 < Z < 1) \approx 0.68$; $P(\mu - \sigma < X < \mu + \sigma) \approx 0.68$.
- $P(-2 < Z < 2) \approx 0.95$; $P(\mu - 2\sigma < X < \mu + 2\sigma) \approx 0.95$.

- Estimate μ and σ^2 when $X \sim \mathcal{N}(\mu, \sigma^2)$.
  - Use the sample mean $\bar{X} = \frac{\sum_{i=1}^n X_i}{n}$ to estimate μ.
  - Use the sample variance $s^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}$ to estimate σ^2.

- Sampling distribution of a sample mean $\bar{X}$:
  - $\bar{X} \sim \mathcal{N}(\mu, \sigma_{\bar{X}}^2 = \frac{\sigma^2}{n})$.
  - We use $\bar{X}$ to estimate the population mean μ.
  - As the population variance σ^2 is usually unknown, we use the sample variance $s^2 = \frac{\sum_{i=1}^n (X_i - \bar{X})^2}{n-1}$ to estimate σ^2 and hence s^2/n to estimate $\sigma_{\bar{X}}^2$.
  - Standard error of $\bar{X}$: $s_{\bar{X}} = \sqrt{\frac{s_X^2}{n}}$.
  - 95% confidence interval of μ (approximately): $\bar{X} \pm 2\sqrt{\frac{s^2}{n}}$.

- Binomial distribution and its normal approximation
  - $X \sim \text{Binomial}(n, p)$ can be approximated with $X \sim \mathcal{N}(np, np(1-p))$ if n is large enough and p is not too close to 0 or 1.
  - Estimate the population proportion p when $X \sim \text{Binomial}(n, p)$, where n is the sample size.
  - Binomial distribution, its normal approximation, and Sampling distribution of a sample proportion $\hat{p}$:
    * Use the sample proportion $\hat{p} = \frac{X}{n}$ to estimate p.
    * Approximately, we have $\hat{p} \sim \mathcal{N}(p, \frac{\hat{p}(1-\hat{p})}{n})$.
    * 95% confidence interval of p: $\hat{p} \pm 2\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$.

- Simple Linear Regression
  - Least squares estimation: given n observations $(x_1, y_1), \cdots, (x_n, y_n)$, we estimate the intercept b_0 and slope b_1 by finding a straight line $\hat{y}_i = b_0 + b_1 x_i$ that minimizes the sum of squared residuals (SSE)

$$\sum_{i=1}^n e_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n \left[y_i - (b_0 + b_1 x_i)\right]^2.$$

  - Sample means of X and Y

$$\bar{x} = \frac{\sum_{i=1}^n x_i}{n}, \quad \bar{y} = \frac{\sum_{i=1}^n y_i}{n}.$$

– Sample covariance

$$\mathrm{Cov}(X,Y) = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{n-1}$$

– Sample correlation

$$r_{xy} = \mathrm{Corr}(X,Y) = \frac{\mathrm{Cov}(X,Y)}{\sqrt{s_x^2 s_y^2}} = \frac{\mathrm{Cov}(X,Y)}{s_x s_y}.$$

$$s_x^2 = \frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1}, \quad s_x = \sqrt{s_x^2}$$

$$s_y^2 = \frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n-1}, \quad s_y = \sqrt{s_y^2}$$

– Estimating the true regression line.

– Least squares estimation:

$$b_0 = \bar{y} - b_1 \bar{x}, \qquad b_1 = r_{xy} \frac{s_y}{s_x}$$

– Interpreting covariance, correlation and regression coefficients.

– SST, SSR, SSE

$$\mathrm{SST} = \sum_{i=1}^n (y_i - \bar{y})^2$$

$$\mathrm{SSR} = \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 = \sum_{i=1}^n \left[(b_0 + b_1 x_i) - \bar{y}\right]^2$$

$$\mathrm{SSE} = \sum_{i=1}^n e_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n \left[y_i - (b_0 + b_1 x_i)\right]^2$$

$$\mathrm{SST} = \mathrm{SSR} + \mathrm{SSE}$$

Note that $\bar{y} = b_0 + b_1 \bar{x}$, $\hat{y}_i = b_0 + b_1 x_i$, $\bar{\hat{y}} = \bar{y}$, and $e_i = y_i - \hat{y}_i = (y_i - \bar{y}) - (\hat{y}_i - \bar{y})$.

– Coefficient of determination:

$$R^2 = \frac{\mathrm{SSR}}{\mathrm{SST}} = 1 - \frac{\mathrm{SSE}}{\mathrm{SST}} = r_{xy}^2$$

– Regression assumptions and statistical model.

$$Y = \beta_0 + \beta_1 X + \epsilon, \ \epsilon \sim \mathcal{N}(0, \sigma^2)$$

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i, \ \epsilon_i \sim \mathcal{N}(0, \sigma^2)$$

$$y_i \sim \mathcal{N}(\beta_0 + \beta_1 x_i, \sigma^2)$$

Assuming β_0, β_1 and σ^2 are known, given x_i, the 95% prediction interval of y_i is

$$(\beta_0 + \beta_1 x_i) \pm 2\sigma.$$

- We estimate σ with the regression standard error s as

$$s = \sqrt{\frac{\sum_{i=1}^{n} e^2}{n-2}} = \sqrt{\frac{SSE}{n-2}}.$$

- Approximately we have $b_1 \sim \mathcal{N}(\beta_1, s_{b_1}^2)$ and $b_0 \sim \mathcal{N}(\beta_0, s_{b_0}^2)$, where the standard errors of b_1 and b_0 are

$$s_{b_1} = \sqrt{\frac{s^2}{(n-1)s_x^2}}, \quad s_{b_0} = \sqrt{s^2 \left(\frac{1}{n} + \frac{\bar{X}^2}{(n-1)s_x^2}\right)}.$$

  Thus approximately we have the 95% confidence intervals for β_1 and β_0 as

$$b_1 \pm 2s_{b_1}, \quad b_0 \pm 2s_{b_0}.$$

- Hypothesis testing:
  * We test the null hypothesis $H_0 : \beta_1 = \beta_1^0$ versus the alternative $H_1 : \beta_1 \neq \beta_1^0$.
  * The t-stat $t = \frac{b_1 - \beta_1^0}{s_{b_1}}$ measures the number of standard errors the estimate b_1 is from the proposed value β_1^0.
  * The p-value provides a measure of how weird your estimate b_1 is if the null hypothesis is true.
  * We usually reject the null hypothesis if $|t| > 2$, $p < 0.05$, or β_1^0 is not within the 95% confidence interval $(b_1 - 2s_{b_1}, b_1 + 2s_{b_1})$.
- Forecasting:
  * Given X_f, the 95% plug-in prediction interval of Y_f is $(b_0 + b_1 X_f) \pm 2s$.
  * A large predictive error variance (high uncertainty) comes from a large s, a small n, a small s_x and a large difference between X_f and $\bar{X}$.

• Multiple Linear Regression

- Statistical model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2)$$

$$Y | X_1 \ldots X_p \sim \mathcal{N}(\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p, \sigma^2)$$

- Interpretation of regression coefficients.
- Fitted values: $\hat{y}_i = b_0 + b_1 x_{i1} + \cdots + b_p x_{ip}$
- Least squares estimation: find b_0, b_1, $\cdots$, b_p that minimize the sum of squared residuals $\sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$.
- Regression standard error:

$$s = \sqrt{\frac{\sum_{i=1}^{n} e_i^2}{n-p-1}} = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n-p-1}}.$$

- $\bar{e} = 0$, $\text{Corr}(X_j, e) = 0$, $\text{Corr}(\hat{Y}, e) = 0$
- $R^2 = \left(\text{Corr}(Y, \hat{Y})\right)^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}$
- Approximately we have $b_j \sim \mathcal{N}(\beta_j, s_{b_j}^2)$.
  * 95% confidence interval for β_j: $b_j \pm 2s_{b_j}$
  * t-stat: $t_j = \frac{b_j - \beta_j^0}{s_{b_j}}$.
  * $H_0 : \beta_j = \beta_j^0$ versus $H_1 : \beta_j \neq \beta_j^0$. Reject H_0 if $|t_j| > 2$, p-value < 0.05, or β_j^0 is not within $(b_j - 2s_{b_j}, b_j + 2s_{b_j})$
- F-test of overall significance.
  * $H_0 : \beta_1 = \beta_2 = \cdots = \beta_p = 0$ versus H_1: at least one $\beta_j \neq 0$.
  * $f = \frac{R^2/p}{(1-R^2)/(n-p-1)} = \frac{SSR/p}{SSE/(n-p-1)}$
  * If H_0 is true, then $f > 4$ is very significant (happens with low probability) in general.
  * If f is large (p-value is small), we reject H_0.
- Understanding multiple linear regression
  * Correlation is not causation
  * Multiple linear regression allows us to control all important variables by including them into the regression model
  * Dependencies between the explanatory variables (X's) will affect our interpretation of regression coefficients
  * Dependencies between the explanatory variables (X's) will inflate the standard errors of regression coefficients

$$s_{b_j}^2 = \frac{s^2}{\text{variation in } X_j \text{ not associated with other } X\text{'s}}$$

- Dummy Variables and Interactions
  - Dummy variables
    * Gender: Male, Female; Education level: High-school, Bachelor, Master, Doctor; Month: Jan, Feb, $\cdots$, Dec
    * A variable of n categories can be included into multiple linear regression using $n - 1$ dummy variables
    * Representing a variable of n categories with n dummy variables will lead to the problem of "perfect multicollinearity"
    * Interpretation: the same slope but different intercepts
  - Interactions
    * Interpretation: different intercepts and slopes
- Diagnostics and Transformations
  - Diagnostics

  * Model assumptions:
    - Statistical model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2)$$

    - The mean of Y is a linear combination of the X's
    - The errors ϵ_i (deviations from the true mean) are independent, and identically normal distributed as $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$
  * Understanding the consequences of violating the model assumptions
  * Detecting and explaining common model assumption violations using the residual plots.
- Modeling non-linearity with polynomial regression
  * Statistical model:

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \cdots + \beta_m X^m + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2)$$

  * We can always increase m if necessary, but $m = 2$ is usually enough.
  * Be very careful about over-fitting and doing prediction outside the data range, especially if m is large.
  * For $Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \epsilon$, the marginal effect of X on Y is

$$\frac{\partial \mathbb{E}[Y|X]}{\partial X} = \beta_1 + 2\beta_2 X,$$

    which means the slope is a function of X (no longer a constant).
- Handing non-constant variance with Log-Log transformation
  * Statistical model:

$$\log(Y) = \beta_0 + \beta_1 \log(X) + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2)$$
$$Y = e^{\beta_0} X^{\beta_1} e^{\epsilon}, \quad \epsilon \sim \mathcal{N}(0, \sigma^2)$$

  * Interpretation: about $\beta_1\%$ change in Y per 1% change in X.
  * Example: price elasticity
  * 95% plug-in prediction interval of $\log(Y)$

$$(\beta_0 + \beta_1 \log(X)) \pm 2s$$

  * 95% plug-in prediction interval of Y

$$\left(e^{\beta_0 + \beta_1 \log(X) - 2s},\ e^{\beta_0 + \beta_1 \log(X) + 2s}\right) = \left(e^{\beta_0 - 2s} X^{\beta_1},\ e^{\beta_0 + 2s} X^{\beta_1}\right)$$

- Log transformation of Y
  * Statistical model:

$$\log(Y) = \beta_0 + \beta_1 X + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2)$$
$$Y = e^{\beta_0} e^{\beta_1 X} e^{\epsilon}, \quad \epsilon \sim \mathcal{N}(0, \sigma^2)$$

        * Interpretation: about $(100\beta_1)\%$ change in Y per unit change in X (if β_1 is small).
        * Example: exponential growth

- Time Series
    - Trend, seasonal, cyclical, and random components of a time series
    - Fitting a trend
        * Linear trend:
$$Y_t = \beta_0 + \beta_1 t + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2)$$
        * Exponential trend:
            · Model: $\log(Y_t) = \beta_0 + \beta_1 t + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2)$
            · Interpretation: Y_t increases by about $(100\beta_1)\%$ per unit time increase.
        * Modeling non-linearity by adding t^2 into the regression model: the slope changes as time changes.
        * 95% plug-in prediction interval
    - Autoregressive models
        * Random walk model: $Y_t = \beta_0 + Y_{t-1} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2)$
        * Autoregressive model of order 1 (AR(1)):
$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2)$$
        * Autocorrelation of residuals: $\mathrm{Corr}(e_t, e_{t-1})$
        * Trend+AR(1):
$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 t + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2)$$
        * Logtransformation + trend + AR(1):
$$\log(Y_t) = \beta_0 + \beta_1 \log(Y_{t-1}) + \beta_2 t + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma^2)$$
    - Modeling seasonality
        * Using 11 dummy variables for 12 months; using 3 dummy variables for 4 quarters
        * Seasonal model:
$$Y_t = \beta_0 + \beta_1 Jan + \cdots + \beta_{11} Nov + \epsilon_t$$
        * Seasonal + AR(1) + linear trend:
$$Y_t = \beta_0 + \beta_1 Jan + \cdots + \beta_{11} Nov + \beta_{12} Y_{t-1} + \beta_{13} t + \epsilon_t$$
            · Model for t in December: $Y_t = \beta_0 + \beta_{12} Y_{t-1} + \beta_{13} t + \epsilon_t$
            · Model for t in Jan: $Y_t = (\beta_0 + \beta_1) + \beta_{12} Y_{t-1} + \beta_{13} t + \epsilon_t$
            · Model for t in October: $Y_t = (\beta_0 + \beta_{10}) + \beta_{12} Y_{t-1} + \beta_{13} t + \epsilon_t$

    - Logtransformation + Seasonal + AR(1) + trend

$$\log(Y_t) = \beta_0 + \beta_1 Jan + \cdots + \beta_{11} Nov + \beta_{12} \log(Y_{t-1}) + \beta_{13} t + \epsilon_t$$

  - Diagnose the residual plot of a time series regression model:
    - Are there any clear temporal patterns?
    - Are the residuals autocorrelated?
    - What kind of model assumptions have been violated?
  - Understand when and how to include log transformation, non-linearity, dummy variables, interactions, AR(1) and trend to improve a time series regression model.

- Model Selection
  - Validate a model using out-of-sample prediction
  - Model selection criteria
  - Stepwise regression

- Decision Making Under Uncertainty
  - Frequency interpretation and subjective interpretation of probability.
  - Probabilities and betting odds
  - Payoff table
  - Bayes' theorem

$$P(A_i|B) = \frac{P(B|A_i)P(A_i)}{P(B|A_1)P(A_1) + \cdots + P(B|A_p)p(A_p)}$$

  - Simpson's paradox
  - Payoffs and losses, loss table
  - Nonprobabilistic decision criteria
    - maximin
    - maximax
    - minimax loss
  - Probabilistic decision criteria: expected payoff (ER) or expected loss (EL)
  - Utility
    - Risk avoider, risk neutral, risk taker
    - A typical utility function: $U(x) = 1 - e^{-x/R}$
  - Decision tree
    - Represent a payoff table with a decision tree
    - Time proceeds from left to right
    - Folding back procedure

        - Risk profile
        - Sensitivity analysis
        - Decision making and Bayes' theorem
    - The value of information
        - Value of perfect information
        - Expected value of perfect information (EVPI)
        - Value of sample information
        - Expected value of sample information (EVSI)
        - Bayes' theorem and the value of information

- Introduction to Monte Carlo Simulation
    - Uniform random numbers
    - Flip a coin, toss a die, flip two coins, toss tow dice
    - Normal random numbers, Student's t random numbers
    - Understand how to simulate from a discrete distribution
    - Understand how to use simulation to estimate $P(X < x)$, $\mathbb{E}[X]$ and $\mathrm{Var}[X]$, where X is a random variable following some distribution.
    - Understand how to use simulation to demonstrate Law of Large Numbers
    - Understand how to use simulation to demonstrate the sampling distribution of sample mean
    - Understand how to use simulation to demonstrate the sampling distribution of sample proportion
    - Understand how to use simulation to demonstrate the Central Limit Theorem
    - Simulation and decision making
    - Simulate an AR(1)+Trend+Logtransformation time series model
    - Using simulation to estimate the prediction intervals
    - Understand how to construct a random experiment and find relevant answers by simulate the same experiment repeatedly under identical conditions