MATH 341: PROBABILITY: FALL 2009 REVIEW SHEET

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ABSTRACT. Below is a summary of definitions and some key lemmas and theorems from Math 341.

1. Chapter 1

- 1.1. **Definitions.** We record some common definitions below.
 - Sample Space (Ω): all possible outcomes. Example: toss coin thrice: $\{HHH, \dots, TTT\}$; toss until get head: $\{H, TH, TTH, \dots\}$.
 - Events: Subsets of sample space Ω . Example: at least 2 of 3 tosses a head: $\{HHT, HTH, THH, HHH\}$.
 - Complement: $A^c = \Omega A$.
 - Field:
 - $\diamond A, B \in \mathcal{F}$ then $A \cup B$ and $A \cap B$ in \mathcal{F} .
 - $\diamond A \in \mathcal{F}$ then $A^c \in \mathcal{F}$.
 - $\diamond \varphi \in \mathcal{F} \text{ (so } \Omega \in \mathcal{F} \text{)}.$
 - \diamond if also $A_i \in \mathcal{F}$ implies $\bigcup_{i=1}^{\infty} A_i \in \mathcal{F}$ then a σ -field.
 - Finitely additive: disjoint union then $\mathbb{P}(\bigcup_{i=1}^n A_i) = \sum_{i=1}^n \mathbb{P}(A_i)$; countably additive if the $\{A_i\}$ pairwise disjoint implies $\mathbb{P}(\bigcup_{i=1}^\infty A_i) = \sum_{i=1}^\infty \mathbb{P}(A_i)$.
 - **Probability space:** A triple $(\Omega, \mathcal{F}, \mathbb{P})$ is a probability space if Ω is a sample space with σ -field \mathcal{F} and a **probability measure** \mathbb{P} satisfying
 - $\diamond \mathbb{P}(\varphi) = 0, \mathbb{P}(\Omega) = 1.$
 - $\diamond \mathbb{P}$ is countably additive: for a disjoint union, $\mathbb{P}(\cup_{i=1}^{\infty}(A_i) = \sum_{i=1}^{\infty}\mathbb{P}(A_i)$.
 - Conditional probability: If $\mathbb{P}(B) > 0$ then the conditional probability of A occurring given B, denoted $\mathbb{P}(A|B)$, is

$$\mathbb{P}(A|B) = \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)}.$$

Date: October 10, 2009.

Interpretation through counting:

$$\frac{N(A\cap B)}{N(B)} \,=\, \frac{N(A\cap B)/N}{N(B)/N} \,\to\, \frac{\mathbb{P}(A\cap B)}{\mathbb{P}(B)}.$$

- \Rightarrow **Example:** roll fair die twice: what is probability of a 7 or an 11 given first roll is 3? Ans: $\frac{1/36}{6/36} = 1/6$ and $\frac{0/36}{6/36} = 0$.
- **Partition** A family of events B_1, \ldots, B_n is a partition of Ω if the $\{B_i\}$'s are disjoint and $\bigcup_{i=1}^n B_i = \Omega$.
- Independence A and B are independent if

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B).$$

More generally, a family $\{A_i\}_{i\in I}$ is independent if

$$\mathbb{P} \left(\bigcap_{i \in J} A_i\right) = \prod_{i \in J} \mathbb{P}(A_i) \text{ for any } J \subset I.$$

1.2. Basic Lemmas.

Lemma 1.1. For a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ we have

- Law of total probability: $\mathbb{P}(A^c) = 1 \mathbb{P}(A)$.
- $A \subset B$ implies $\mathbb{P}(A) \leq \mathbb{P}(B) = \mathbb{P}(A) + \mathbb{P}(B A)$.
- $\mathbb{P}(A \cup B) = \mathbb{P}(A) + \mathbb{P}(B) \mathbb{P}(A \cap B)$.
- $\mathbb{P}(\bigcup_{i=1}^n A_i) = \sum_{i=1}^n \mathbb{P}(A_i) \sum_{i < j} \mathbb{P}(A_i \cap A_j) + \dots + (-1)^{n+1} \mathbb{P}(A_1 \cap \dots \cap A_n)$ (Inclusion Exclusion Principle).

Lemma 1.2. $A_1 \subset A_2 \subset \cdots$ and $B_1 \supset B_2 \supset \cdots$, then

- If $A = \bigcup_{i=1}^{\infty} A_i$ then $\mathbb{P}(A) = \lim_{n \to \infty} \mathbb{P}(\bigcup_{i=1}^n A_i)$.
- If $B = \bigcap_{i=1}^{\infty} B_i$ then $\mathbb{P}(B) = \lim_{n \to \infty} \mathbb{P}(\bigcap_{i=1}^n B_i)$.

Lemma 1.3. If $0 < \mathbb{P}(B) < 1$ then for any event A we have

$$\mathbb{P}(A) = \mathbb{P}(A|B)\mathbb{P}(B) + \mathbb{P}(A|B^c)\mathbb{P}(B^c).$$

If the $\{B_i\}$ form a pairwise disjoint partition, then

$$\mathbb{P}(A) = \sum_{i=1}^{n} \mathbb{P}(A|B_i)\mathbb{P}(B_i).$$

2. Chapter 2

2.1. **Definitions.**

- Random Variables: Consider a probability space $(\Omega, \mathcal{F}, \mathbb{P})$. A random variable is a function X from the sample space Ω to the real numbers with the property that $\{\omega \in \Omega : X(\omega) \leq x\} \in \mathcal{F}$ for each x.
- **Distribution Function:** The distribution function of a random variable $X: \Omega \to \mathbb{R}$ is the function $F: \mathbb{R} \to [0,1]$ given by $F(x) = \mathbb{P}(X \le x)$. In other words, it's the probability of observing a value of X of at most x.
 - \diamond **Example:** Consider five tosses of a fair coin. We have F(0)=1/32, F(1)=6/32, F(2)=16/32, F(3)=26/32, F(4)=31/32 and F(5)=32/32. Our function is supposed to be defined for all real x, so what we really have is the following: F(x)=0 if x<0, F(x)=1/32 if $0\le x<1$, F(x)=6/32 if $1\le x<2$, and so on.
- **Discrete Random Variables:** A random variable X is discrete if it takes values in a countable subset $\{x_1, x_2, \dots\}$ of \mathbb{R} . It has probability mass function $f: \mathbb{R} \to [0, 1]$ given by $f(x) = \mathbb{P}(X = x)$.
 - \diamond **Example:** Toss a fair coin until the first head is obtained. Then $\Omega = \{H, TH, TTH, \dots\}$. Let X be the number of tosses needed to obtain the first head. Then X is discrete, taking on the values $\{1, 2, 3, \dots\}$, with the probability X equals n just $1/2^n$.
- Continuous Random Variables: A random variable X is continuous if its distribution function can be written as $F(x) = \int_{-\infty}^{x} f(u) du$ for some integrable function f (which is called the probability density function of X).
 - \diamond **Example:** Let $\Omega = [0,1]$ and let $\mathcal F$ be the σ -field generated by the open intervals. (This is the standard σ -field.) Let $X(\omega)$ equal ω^2 . If we let Y be uniformly distributed on [0,1], then we see $\mathbb P(X \le x)$ is the same as $\mathbb P(Y \le \sqrt x)$, which is just $\sqrt x$. We are therefore looking for f so that $\sqrt x = \int_0^x f(u) du$ for $0 \le x \le 1$. Differentiating both sides gives $\frac{1}{2}x^{-1/2} = f(x)$ (note the integral is $\mathfrak F(x) \mathfrak F(0)$ with $\mathfrak F$ any anti-derivative of f; differentiating yields the claim as $\mathfrak F' = f$). We see that for our random variable X, we may take $f(u) = 1/2\sqrt u$ for $0 < u \le 1$ and 0 otherwise.

- Joint Distribution of a Random Vector: The joint distribution function of a random vector $\overrightarrow{\mathbf{X}} = (X_1, \dots, X_n)$ on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$ is the function $F_{\overrightarrow{\mathbf{X}}}: \mathbb{R}^n \to [0,1]$ given by $F_{\overrightarrow{\mathbf{X}}}(\overrightarrow{x}) = \mathbb{P}(\overrightarrow{\mathbf{X}} \leq \overrightarrow{x})$ for $\overrightarrow{x} \in \mathbb{R}^n$, where $\overrightarrow{x} \leq \overrightarrow{y}$ means each $x_i \leq y_i$, and $\{\overrightarrow{\mathbf{X}} \leq \overrightarrow{x}\} = \{\omega \in \Omega : \overrightarrow{\mathbf{X}}(\omega) \leq \overrightarrow{x}\}.$
- Jointly Discrete X_1, \ldots, X_n random vectors on $(\Omega, \mathcal{F}, \mathbb{P})$ are jointly discrete if $\overrightarrow{\mathbf{X}} = (X_1, \dots, X_n)$ takes values in a countable subset of \mathbb{R}^n and has joint probability mass function $f: \mathbb{R}^n \to [0,1]$ given by

$$f(x_1,\ldots,x_n) = \mathbb{P}(X_1 = x_1,\ldots,X_n - x_n).$$

• Jointly Continuous Jointly continuous defined analogously, with

$$F_{\overrightarrow{\mathbf{X}}}(\overrightarrow{x}) = \int_{u_1=-\infty}^{x_1} \cdots \int_{u_n=-\infty}^{x_n} f(u_1, \dots, u_n) du_1 \cdots du_n$$

for some integrable function $f: \mathbb{R}^n \to [0, \infty)$.

• Marginals: Same set-up as above, the j^{th} marginal F_{X_i} is defined by

$$F_{X_j}(x_j) := \lim_{x_1,\dots,x_{j-1},x_{j+1},\dots,x_n \to \infty} F_{\overrightarrow{\mathbf{X}}}(\overrightarrow{x}).$$

2.2. Lemmas.

Lemma 2.1. The (cumulative) distribution function satisfies the properties:

- $\lim_{x_1,\dots,x_n\to-\infty}F_{\overrightarrow{X}}(\overrightarrow{x})=0$, $\lim_{x_1,\dots,x_n\to\infty}F_{\overrightarrow{X}}(\overrightarrow{x})=1$. If $\overrightarrow{x}\leq\overrightarrow{x}'$ then $F_{\overrightarrow{X}}(\overrightarrow{x})\leq F_{\overrightarrow{X}}(\overrightarrow{x}')$. $F_{\overrightarrow{X}}$ continuous from above.

3. Chapters 3 and 4

3.1. **Definition.**

- **Probability Mass Function:** The Probability Mass Function of a discrete random variable X is a function $f: \mathbb{R} \to [0, 1]$ given by $f(x) = \mathbb{P}(X = x)$.
- **Probability Density Function:** The Probability Density Function of a continuous random variable X is the f such that $F(x) = \int_{-\infty}^{x} f(u) du$.
- Independence of events: Two events A and B are independent if $\mathbb{P}(A \cap B) =$ $\mathbb{P}(A)\mathbb{P}(B)$.
 - \diamond As $\mathbb{P}(A \cap B) = \mathbb{P}(A|B)\mathbb{P}(B)$, if $\mathbb{P}(B) > 0$ this is equivalent to $\mathbb{P}(A|B) =$ $\mathbb{P}(A)$, or that knowledge of one happening does not affect knowledge of the

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other happening.

- Independence of random variables: Two random variables X and Y are independent if for all x, y:
 - \diamond **Discrete case:** events $\{X = x\}$ and $\{Y = y\}$ are independent.
 - \diamond Continuous case: events $\{X \leq x\}$ and $\{Y \leq y\}$ are independent.
- Expectation (mean value, average): X random variable with density / mass function f_X , then expected value is

 - ♦ **Discrete case:** $\mathbb{E}[X] := \sum_x x f_X(x)$ if sum converges absolutely. ♦ **Continuous case:** $\mathbb{E}[X] := \int_{-\infty}^{\infty} x f_X(x) dx$ if integral converges absolutely.
- Moments: Let X be a random variable. We define $\diamond k^{\text{th}}$ moment: $m_k := \mathbb{E}[X^k]$ (if converges absolutely).
- Assume X has a finite mean, which we denote by μ (so $\mu = \mathbb{E}[X]$). We define $\diamond k^{\text{th}}$ centered moment: $\sigma_k := \mathbb{E}[(X - \mu)^k]$ (if converges absolutely).
- Variance: Call σ_2 the variance, write it as σ^2 . Note $\sigma^2 = \mathbb{E}[(X \mu)^2] =$ $\mathbb{E}[X^2] - \mathbb{E}[X]^2$.

3.2. Lemmas.

Lemma 3.1. Standard properties of the probability mass function:

- $F(x) = \sum_{x_i \le x} f(x_i)$, and $f(x) = F(x) \lim_{y \to x^-} F(y)$. $\{x : f(x) \ne 0\}$ is at most countable.
- $\sum_{i} f(x_i) = 1$ where $\{x_1, x_2, \dots\}$ is where f is non-zero.

Lemma 3.2. *Standard properties of the probability density function:*

- $\mathbb{P}(a \le X \le b) = \int_a^b f(x) dx$.

Lemma 3.3. Let $q, h : \mathbb{R} \to \mathbb{R}$ and assume X and Y are independent random variables. Then g(X) and h(Y) are independent.

Lemma 3.4 (Key results). Let X and Y be two random variables, and let $a, b \in \mathbb{R}$.

- Linearity: $\mathbb{E}[aX + bY] = a\mathbb{E}[X] + b\mathbb{E}[Y]$.
- Independence: X, Y independent then $\mathbb{E}[XY] = \mathbb{E}[X]\mathbb{E}[Y]$. If RHS holds say uncorrelated.