# 18.175: Lecture 4 Integration

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Expectation

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- Measure  $\mu$  is **probability measure** if  $\mu(\Omega) = 1$ .
- The Borel σ-algebra B on a topological space is the smallest σ-algebra containing all open sets.

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- ▶ Note: to prove X is measurable, it is enough to show that the pre-image of every open set is in *F*.
- Can talk about σ-algebra generated by random variable(s): smallest σ-algebra that makes a random variable (or a collection of random variables) measurable.

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  - ▶ *f* is non-negative (hint: reduce to previous case by taking  $f \land N$  for  $N \to \infty$ ).
  - f is any measurable function (hint: treat positive/negative parts separately, difference makes sense if both integrals finite).

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  - If g = f a.e. then  $\int g d\mu = \int f d\mu$ .

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• When  $(\Omega, \mathcal{F}, \mu) = (\mathbb{R}^d, \mathcal{R}^d, \lambda)$ , write  $\int_E f(x) dx = \int 1_E f d\lambda$ .

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- $EX^k$  is called *k*th moment of *X*. Also, if m = EX then  $E(X m)^2$  is called the variance of *X*.