### 18.600: Lecture 8

## Discrete random variables

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## Outline

Defining random variables

Probability mass function and distribution function

Recursions

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# Defining random variables 

## Probability mass function and distribution function

## Recursions

## Random variables

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- Question: What is $P\{X=k\}$ in this case?
- Answer: $\binom{n}{k} / 2^{n}$, if $k \in\{0,1,2, \ldots, n\}$.


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- Does pairwise independence imply independence?
- No. Consider these three events: first coin heads, second coin heads, odd number heads. Pairwise independent, not independent.


## Examples

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- Then $\sum_{i=1}^{n} 1_{E_{i}}$ is total number of people who get own hats.
- Writing random variable as sum of indicators: frequently useful, sometimes confusing.


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- $1-(1 / 2)^{k}$


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- Answer: Didn't specify. One possibility would be to define state space as $S=\{0,1,2, \ldots\}$ and define $X$ (as a function on $S$ ) by $X(j)=j$. The probability function would be determined by $P(S)=\sum_{k \in S} e^{-\lambda} \lambda^{k} / k!$.


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- Are there other choices of $S$ and $P$ - and other functions $X$ from $S$ to $P$ - for which the values of $P\{X=k\}$ are the same?
- Yes. " $X$ is a Poisson randorf²variable with intensity $\lambda$ " is statement only about the probability mass function of $X$.


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- Famous correspondence by Fermat and Pascal. Led Pascal to write Le Triangle Arithmétique.

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