# Marginalization and Independence 

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## Marginalization

If we know a joint distribution of multiple variables, what if we want to know the distribution of only one of the variables?

We can compute the distribution of $P(X)$ from $P(X, Y, Z)$ through marginalization:

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\sum_{y} \sum_{z} P(X=x, Y=y, Z=z)=P(X)
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We'll explain this notation more next week for now the formula is the most important part.

## Marginalization (from Leyton-Brown)

| Joint distribution |  |  |  |
| :---: | :---: | :---: | :---: |
| temperature ( T ) and weather ( W ) |  |  |  |
|  | $\mathrm{T}=\mathrm{Hot}$ | T=Mild | T=Cold |
| W=Sunny | . 10 | . 20 | . 10 |
| W=Cloudy | . 05 | . 35 | . 20 |

Marginalization allows us to compute distributions over smaller sets of variables:

- $P(X, Y)=\sum_{z} P(X, Y, Z=z)$
- Corresponds to summing out a table dimension
- New table still sums to 1


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- Marginalize out weather

$$
\text { T=Hot } \quad \text { T=Mild } \quad \text { T=Cold }
$$

- Marginalize out temperature


## Marginalization (from Leyton-Brown)

Joint distribution

| temperature $(T)$ and weather $(W)$ |  |  |  |
| :--- | :---: | :---: | :---: |
|  | $\mathrm{T}=$ Hot | $\mathrm{T}=$ Mild | $\mathrm{T}=$ Cold |
| $\mathrm{W}=$ Sunny | .10 | .20 | .10 |
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| $l$ |  |  |  |
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| T=Hot | T=Mild | T=Cold |
| :---: | :---: | :---: |
| .15 | .55 | .30 |

- Marginalize out temperature


## Marginalization (from Leyton-Brown)

## Joint distribution

temperature ( T ) and weather ( W )

|  | T=Hot | T=Mild | T=Cold |
| :---: | :---: | :---: | :---: |
| W=Sunny | .10 | .20 | .10 |
| W=Cloudy | .05 | .35 | .20 |

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- $P(X, Y)=\sum_{z} P(X, Y, Z=z)$
- Marginalize out weather

| T=Hot | T=Mild | $\mathrm{T}=$ Cold |
| :---: | :---: | :---: |
| .15 | .55 | .30 |

- Marginalize out temperature W=Sunny
W=Cloudy
- Corresponds to summing out a table dimension
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## Marginalization (from Leyton-Brown)

## Joint distribution

temperature ( T ) and weather ( W )

|  | T=Hot | T=Mild | T=Cold |
| :---: | :---: | :---: | :---: |
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| T=Hot | T=Mild | $\mathrm{T}=$ Cold |
| :---: | :---: | :---: |
| .15 | .55 | .30 |

- Marginalize out temperature W=Sunny
W=Cloudy
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## Marginalization (from Leyton-Brown)

## Joint distribution

temperature ( T ) and weather ( W )

|  | T=Hot | T=Mild | T=Cold |
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| W=Sunny | .10 | .20 | .10 |
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Marginalization allows us to compute distributions over smaller sets of variables:

- $P(X, Y)=\sum_{z} P(X, Y, Z=z)$
- Marginalize out weather

| $\mathrm{T}=$ Hot | $\mathrm{T}=$ Mild | $\mathrm{T}=$ Cold |
| :---: | :---: | :---: |
| .15 | .55 | .30 |

- Marginalize out temperature W=Sunny . 40
W=Cloudy
- Corresponds to summing out a table dimension
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## Marginalization (from Leyton-Brown)

## Joint distribution

temperature ( T ) and weather ( W )

|  | T=Hot | T=Mild | T=Cold |
| :---: | :---: | :---: | :---: |
| W=Sunny | .10 | .20 | .10 |
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- $P(X, Y)=\sum_{z} P(X, Y, Z=z)$
- Marginalize out weather

| T=Hot | T=Mild | $\mathrm{T}=$ Cold |
| :---: | :---: | :---: |
| .15 | .55 | .30 |

- Marginalize out temperature W=Sunny . 40
W=Cloudy . 60
- Corresponds to summing out a table dimension
- New table still sums to 1


## Independence

Random variables $X$ and $Y$ are independent if and only if $P(X=x, Y=y)=P(X=x) P(Y=y)$.
Mathematical examples:

- If I flip a coin twice, is the second outcome independent from the first outcome?


## Independence

Random variables $X$ and $Y$ are independent if and only if $P(X=x, Y=y)=P(X=x) P(Y=y)$.
Mathematical examples:

- If I flip a coin twice, is the second outcome independent from the first outcome?
- If I draw two socks from my (multicolored) laundry, is the color of the first sock independent from the color of the second sock?


## Independence

Intuitive Examples:

- Independent:
- you use a Mac / the Green Line is on schedule
- snowfall in the Himalayas / your favorite color is blue


## Independence

Intuitive Examples:

- Independent:
- you use a Mac / the Green Line is on schedule
- snowfall in the Himalayas / your favorite color is blue
- Not independent:
- you vote for Larry Hogan / you are a Republican
- there is a traffic jam Baltimore / there's a home game


## Independence

Sometimes we make convenient assumptions.

- the values of two dice (ignoring gravity!)
- the value of the first die and the sum of the values
- whether it is raining and the number of taxi cabs
- whether it is raining and the amount of time it takes me to hail a cab
- the first two words in a sentence

