

# Sampling in sequence models

© 2019 Philipp Krähenbühl and Chao-Yuan Wu

# Sampling

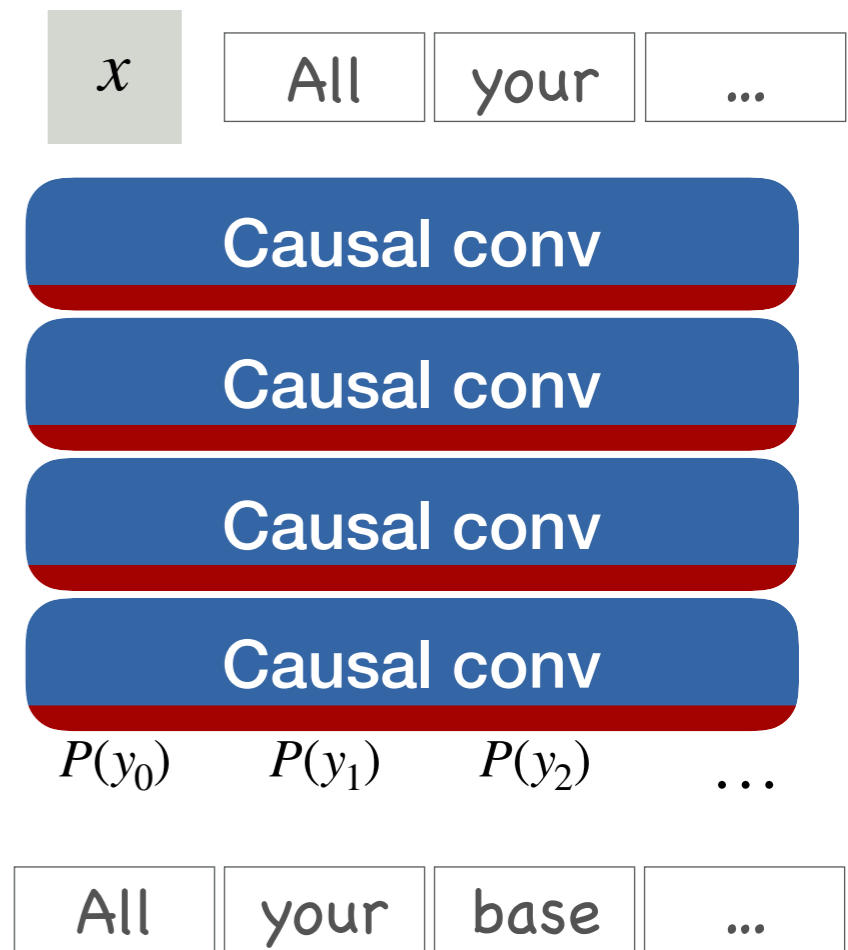
- Example temporal convolutional network

- Autoregressive

$$P(y_0, y_1, y_2, \dots) = P(y_0 | x) \cdot P(y_1 | x, y_0) \cdot P(y_2 | x, y_0, y_1) \cdot \dots$$

- Objective find

- $\hat{y} = \arg \max_y P(y_0, y_1, y_2, \dots)$



# Greedy sampling

$$P(y_0, y_1, y_2, \dots) = P(y_0 | x) \cdot \\ P(y_1 | x, y_0) \cdot \\ P(y_2 | x, y_0, y_1) \cdot \\ \dots$$

- Pick sequentially

$$\hat{y}_t = \arg \max_{y_t} P(y_t | x, \hat{y}_0, \hat{y}_1, \dots)$$

- Single sample
- Not optimal

# Sequential sampling

$$P(y_0, y_1, y_2, \dots) = P(y_0 | x) \cdot$$

$$P(y_1 | x, y_0) \cdot$$

$$P(y_2 | x, y_0, y_1) \cdot$$

...

- For n iterations
  - Sample sequentially  
 $\hat{y}_t \sim P(y_t | x, \hat{y}_0, \hat{y}_1, \dots)$
- Unbiased sampling
  - Not sample efficient

# Beam search

- Biased sampling
  - High likelihood samples
- Generally works best
  - Keep top k samples  $S$ 
    - Largest  $P(y_0)$
  - For  $t$  steps
    - For each  $\hat{y}_0, \hat{y}_1, \dots \in S$ 
      - Compute  $P(x, \hat{y}_0, \hat{y}_1, \dots, y_t)$
    - Keep top k samples  $S$