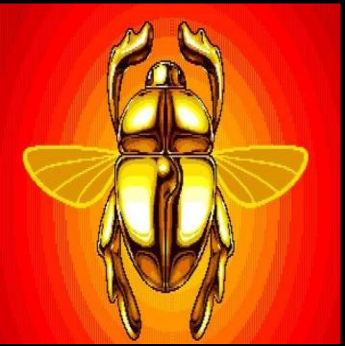


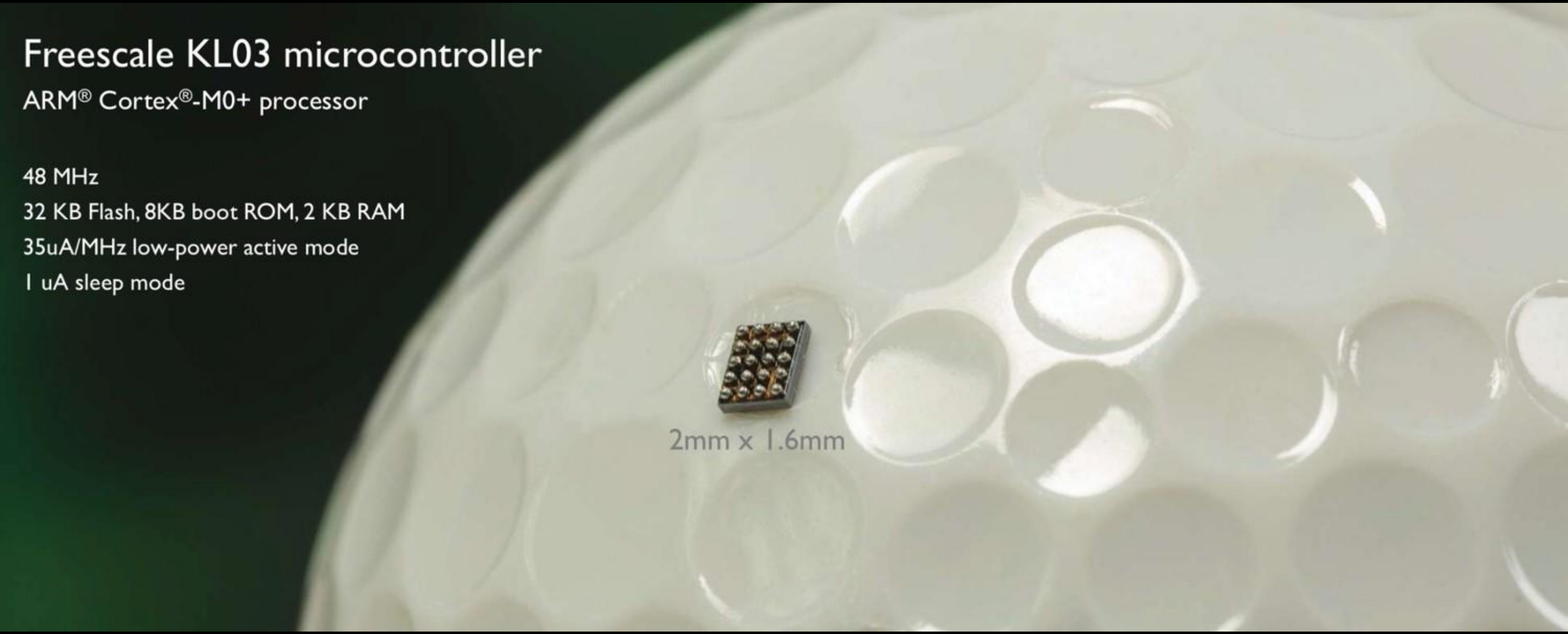

The Edge of Machine Learning

Resource-efficient ML in 2 KB RAM for the Internet of Things

Aditya Kusupati & Don Dennis
Microsoft Research India

D. Dennis, S. Gopinath, P. Jain, A. Kusupati, N. Natarajan, S. Patil, R. Sharma, H. Simhadri & M. Varma

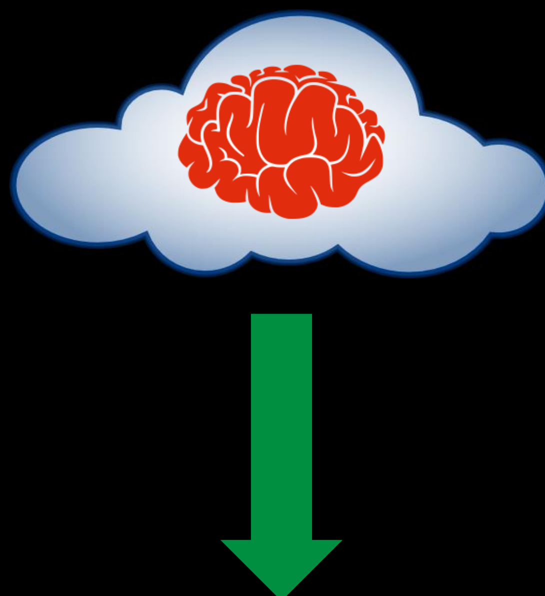
Resource-constrained IoT Devices



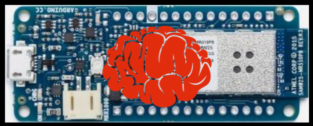
ARM Cortex M0+ at 48 MHz & 35 μA/MHz
with 2 KB RAM & 32 KB read only Flash

Edge Machine Learning – Objectives

- To build a library of machine learning algorithms
  - Which can be trained in the cloud
  - But which will run on tiny IoT devices



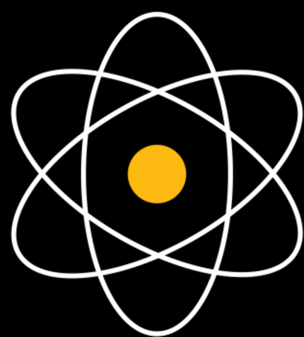
ARM Cortex M0+



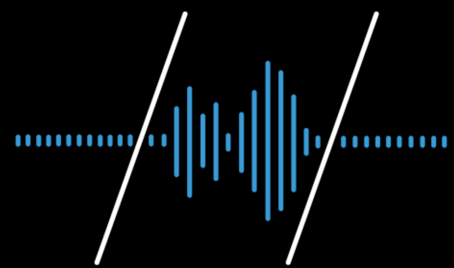
Microsoft’s EdgeML Library

- Compact tree, kNN and RNN algorithms for classification, regression, ranking, time series *etc*.,

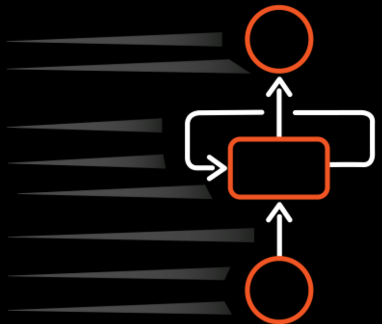
Bonsai



ProtoNN



EMI-RNN



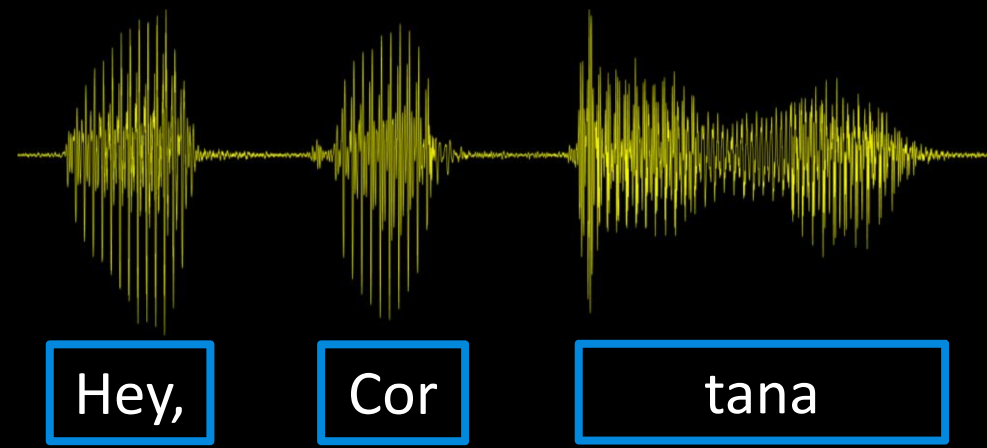
FastGRNN

https://github.com/Microsoft/EdgeML

Time Series

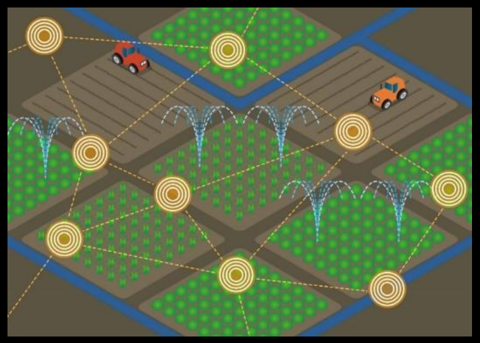
- Time series are the most frequently occurring types of signals found in the IoT domain

“Hey, Cortana”

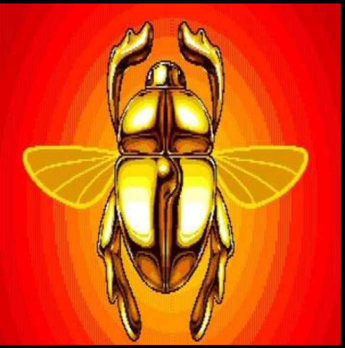


Sprinklers

Soil moisture during a day



Smart farm



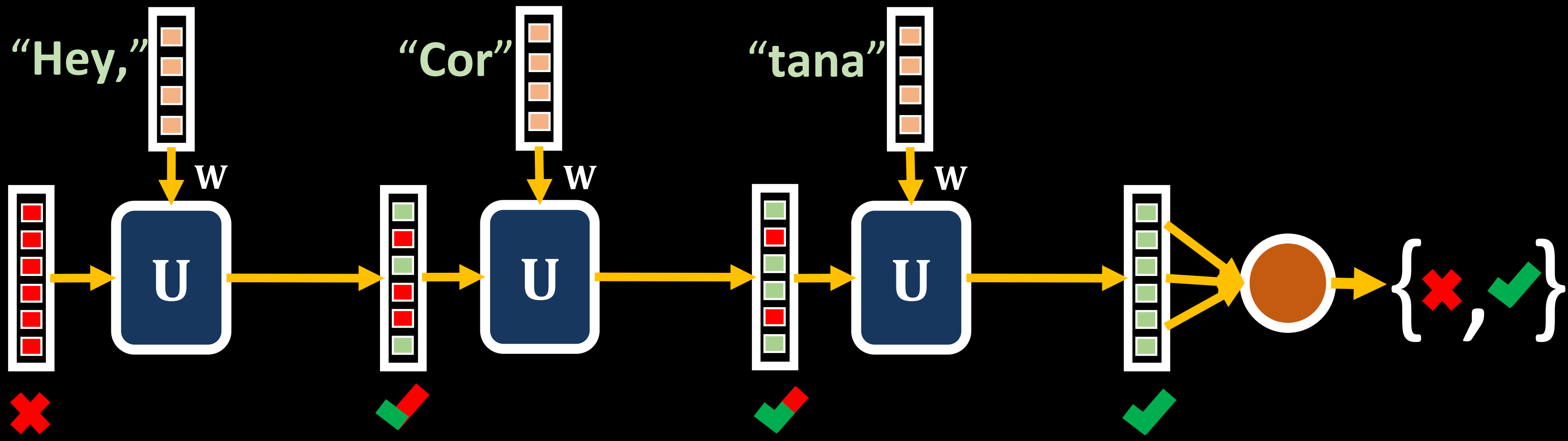

FastGRNN

A Fast, Accurate, Stable & Tiny (Kilobyte Sized) Gated RNN

A. Kusupati (MSRI), M. Singh (IITD), K. Bhatia (Berkeley), A. Kumar (Berkeley), P. Jain (MSRI) & M. Varma (MSRI)

Recurrent Neural Networks (RNNs)

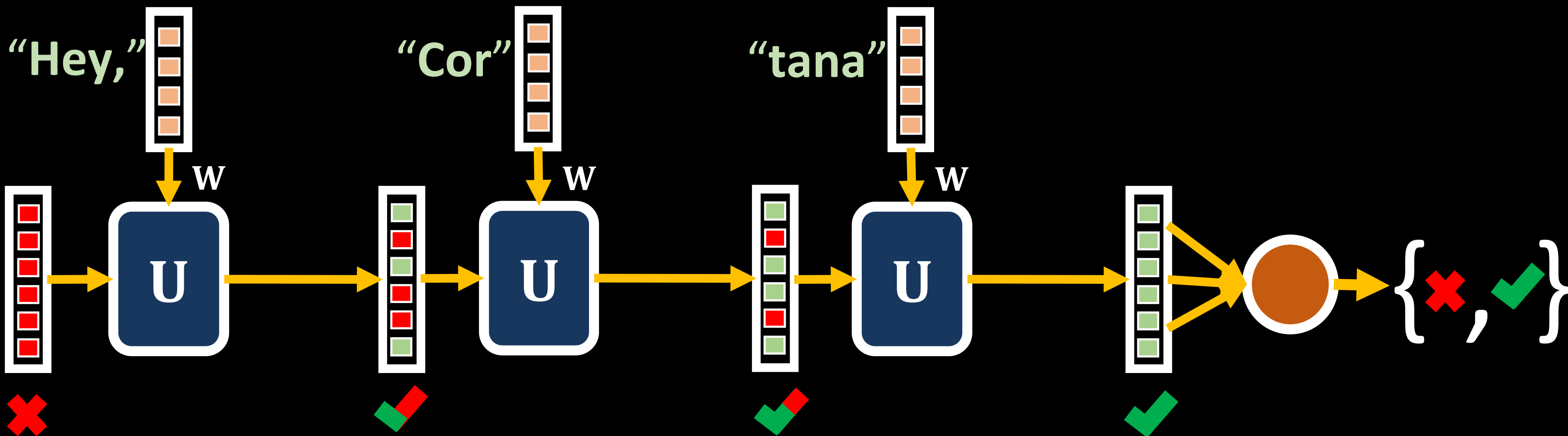
- State-of-the-art for analyzing sequences & time series
- Training is unstable due to exploding & vanishing gradients



$$\mathbf{h}_t = \sigma(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b})$$

Recurrent Neural Networks (RNNs)

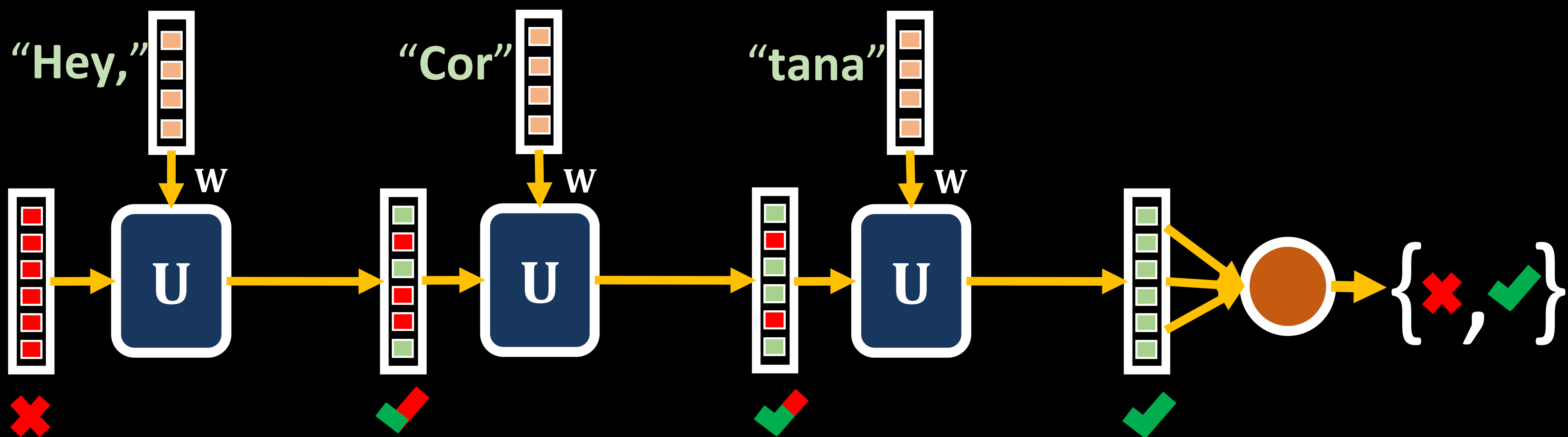
- State-of-the-art for analyzing sequences & time series
- Training is unstable due to exploding & vanishing gradients



$$\nabla = f\left(\ldots, \mathbf{U}^T = \mathbf{Q} \begin{bmatrix} 1.2^{100} & & \\ & \ddots & \\ & & 0.8^{100} \end{bmatrix} \mathbf{Q}^\top, \ldots\right)$$

Unitary RNNs – uRNN, SpectralRNN, …

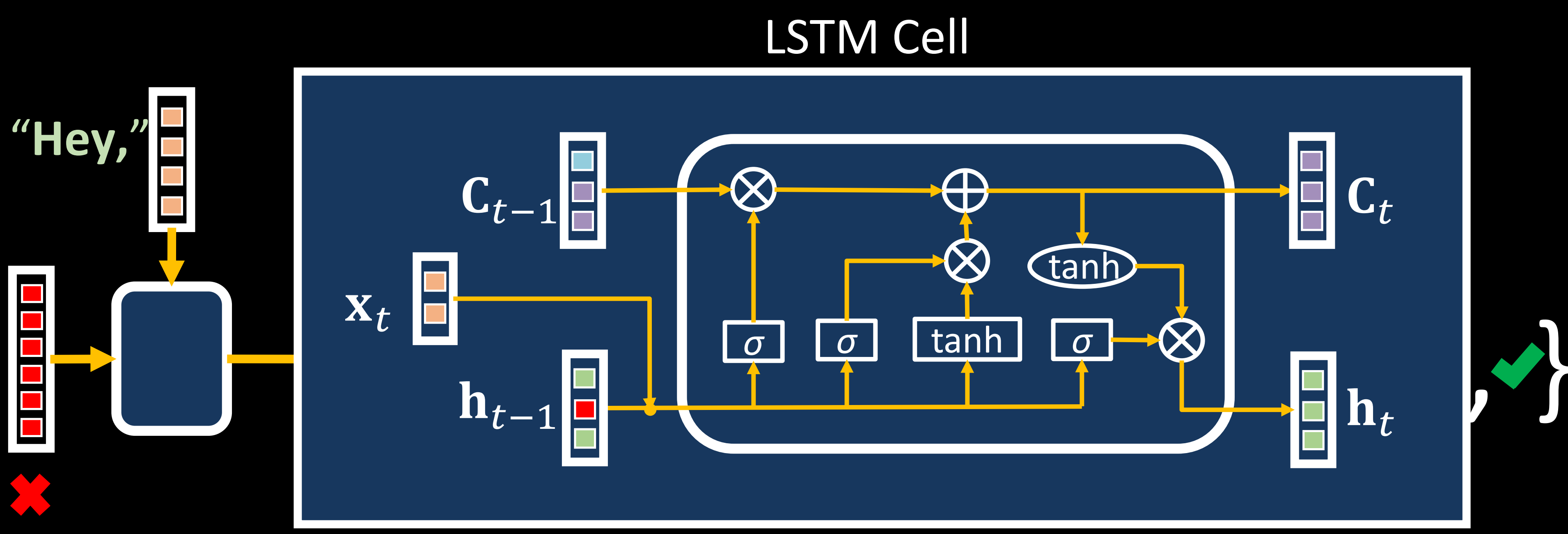
- Unitary RNNs force all the eigenvalues of $\mathbf{U}$ to be ≈ 1
- Unfortunately, they are expensive to train & lack accuracy



$$\nabla = \ f(\ldots, \mathbf{U}^T = \mathbf{Q}\begin{bmatrix} 1^T & & \\ & \ddots & \\ & & 1^T \end{bmatrix}\mathbf{Q}^\top, \ldots)$$

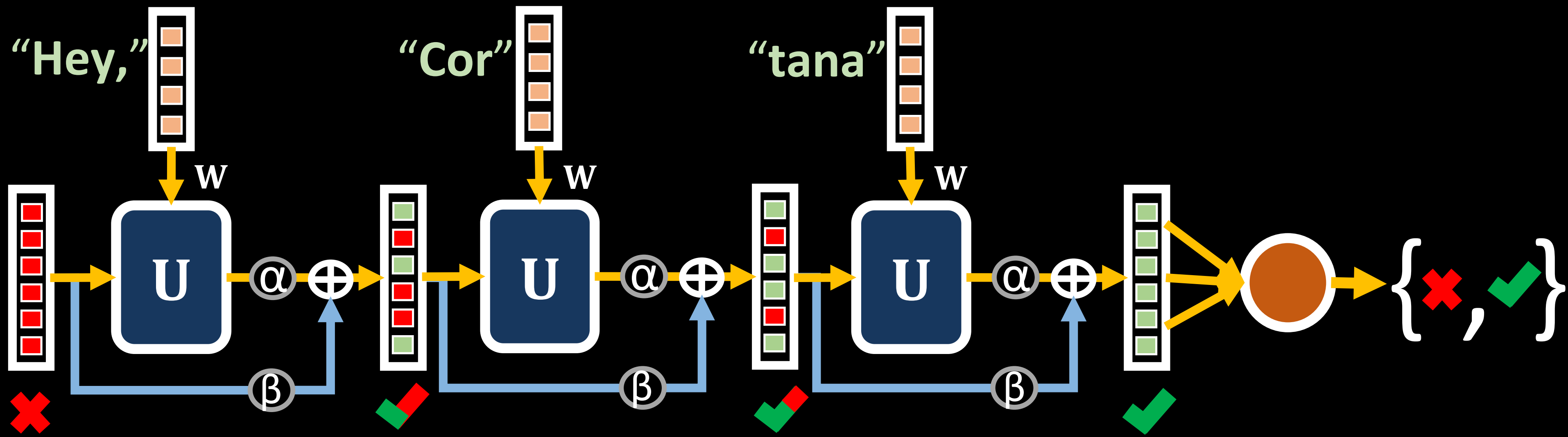
Gated RNNs – LSTM, GRU, …

- Add extra parameters to stabilize training
- Have increased prediction costs on IoT microcontrollers
- Have intuitive explanations but lack formal guarantees



FastRNN

- Provably stable training with 2 additional scalars
- Accuracy: RNN ≪ Unitary RNNs < FastRNN < Gated RNNs



$$\widetilde{\mathbf{h}_t} = \sigma(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b})$$
$$\mathbf{h}_t = \alpha\widetilde{\mathbf{h}_t} + \beta\mathbf{h}_{t-1}$$

RNN gradients

$$\boxed{\mathbf{h}_t = \sigma(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b})}$$

$$\frac{\partial L}{\partial \mathbf{U}} = \sum_{\mathrm{t}=0}^{\mathrm{T}} \mathbf{D}_{\mathrm{t}} \left(\prod_{\mathrm{k}=\mathrm{t}}^{\mathrm{T}-1} \mathbf{U}^{\intercal} \mathbf{D}_{\mathrm{k}+1} \right) \left(\nabla_{\mathbf{h}_{\mathrm{T}}} L \right) \mathbf{h}_{\mathrm{t}-1}^{\intercal}$$

$$\frac{\partial L}{\partial \mathbf{W}} = \sum_{\mathrm{t}=0}^{\mathrm{T}} \mathbf{D}_{\mathrm{t}} \left(\prod_{\mathrm{k}=\mathrm{t}}^{\mathrm{T}-1} \mathbf{U}^{\intercal} \mathbf{D}_{\mathrm{k}+1} \right) \left(\nabla_{\mathbf{h}_{\mathrm{T}}} L \right) \mathbf{x}_{\mathrm{t}}^{\intercal}$$

$$\mathbf{D}_k = \mathrm{grad}(\mathbf{h}_k)$$

$$\mathbf{D}_k = \mathrm{diag}(\sigma'(\mathbf{W}\mathbf{x}_k + \mathbf{U}\mathbf{h}_{k-1} + \mathbf{b}))$$

FastRNN gradients

$$\boxed{\begin{gathered}\tilde{\mathbf{h}}_t = \sigma(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b}) \\ \mathbf{h}_t = \alpha\tilde{\mathbf{h}}_t + \beta\mathbf{h}_{t-1}\end{gathered}}$$

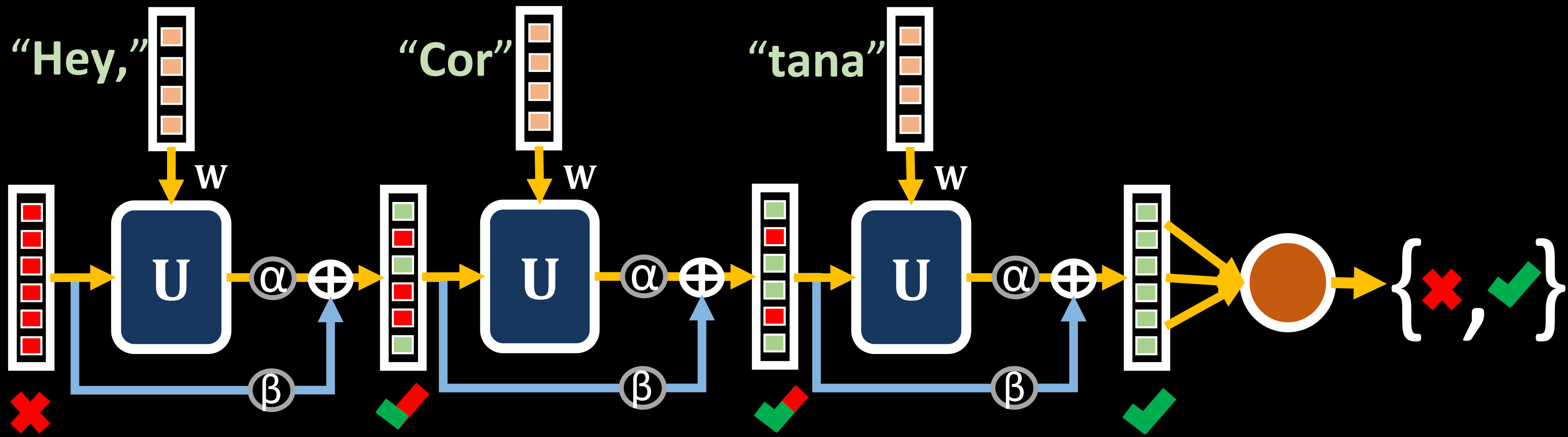
$$\frac{\partial L}{\partial \mathbf{U}} = \alpha \sum_{t=0}^{T} \mathbf{D}_t \left(\prod_{k=t}^{T-1} (\alpha \mathbf{U}^\intercal \mathbf{D}_{k+1} + \beta \mathbf{I}) \right) (\nabla_{\mathbf{h}_T} L) \mathbf{h}_{t-1}^\intercal$$

$$\frac{\partial L}{\partial \mathbf{W}} = \alpha \sum_{t=0}^{T} \mathbf{D}_t \left(\prod_{k=t}^{T-1} (\alpha \mathbf{U}^\intercal \mathbf{D}_{k+1} + \beta \mathbf{I}) \right) (\nabla_{\mathbf{h}_T} L) \mathbf{x}_{t}^\intercal$$

$$\mathbf{D}_k = \mathrm{grad}(\tilde{\mathbf{h}}_k) \qquad \mathbf{D}_k = \mathrm{diag}(\sigma'(\mathbf{W}\mathbf{x}_k + \mathbf{U}\mathbf{h}_{k-1} + \mathbf{b}))$$

FastRNN

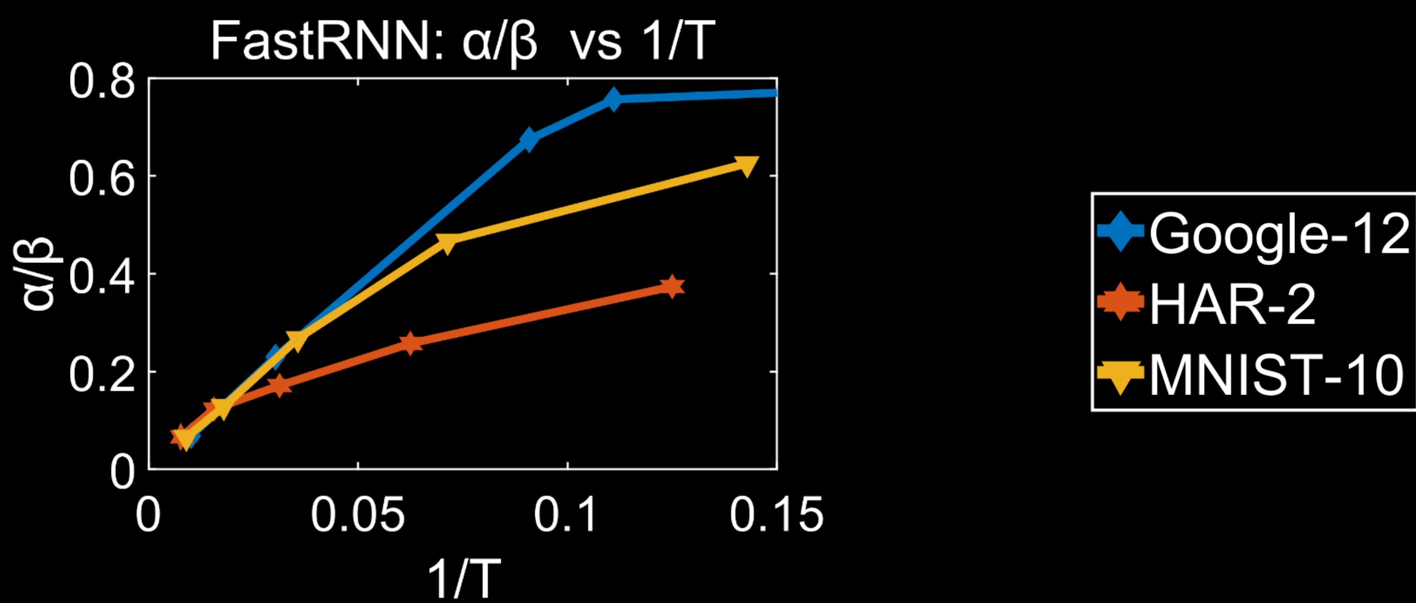
- Provably stable training with 2 additional scalars
- Accuracy: RNN ≪ Unitary RNNs < FastRNN < Gated RNNs



$$\nabla = \; f\left(\ldots, (\alpha\mathbf{UD} + \beta\mathbf{I})^T = \mathbf{Q}\begin{bmatrix}(\beta + \alpha\|\mathbf{UD}\|)^T & & \\ & \ddots & \\ & & (\beta - \alpha\|\mathbf{UD}\|)^T\end{bmatrix}\mathbf{Q}^\top, \ldots\right)$$

Theoretical Analysis of FastRNN

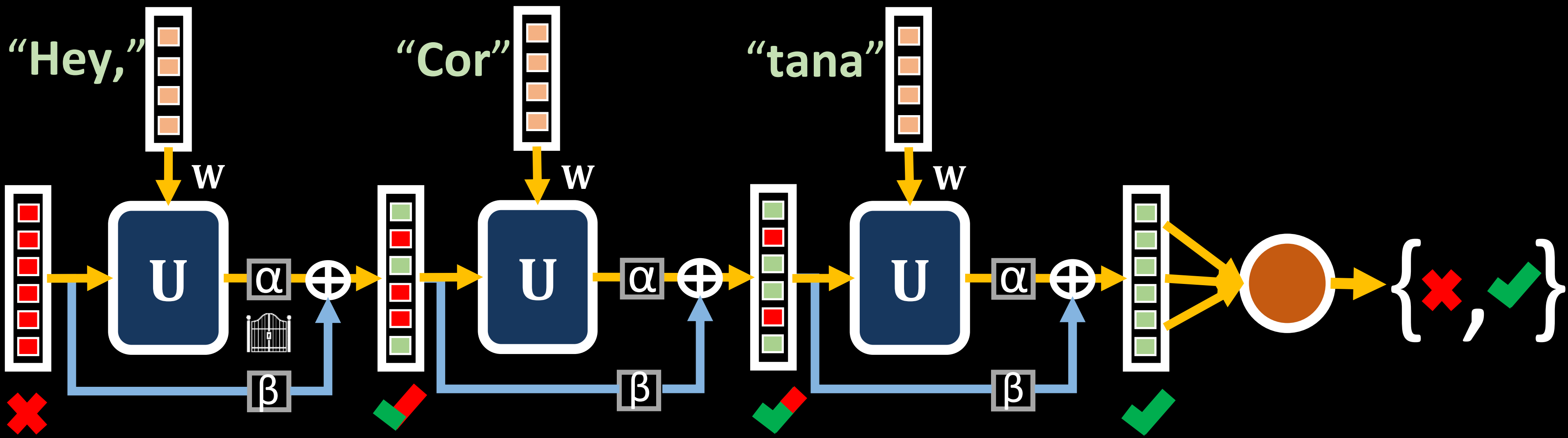
- Convergence & generalization error bounds
  - FastRNN is independent of T when $\alpha/\beta \approx O(1/T)$
  - A similar analysis reveals that an RNN is exponential in T



- FastRNN converges to within ϵ of a stationary point in $O(1/_{\epsilon^2})$ SGD iterations and its generalization error is bounded by $O(\frac{1}{\sqrt{n}})$

FastGRNN

- Extend α & β from scalars to vector gates
- Accuracy: RNN ≪ Unitary RNNs < Gated RNNs ≈ FastGRNN

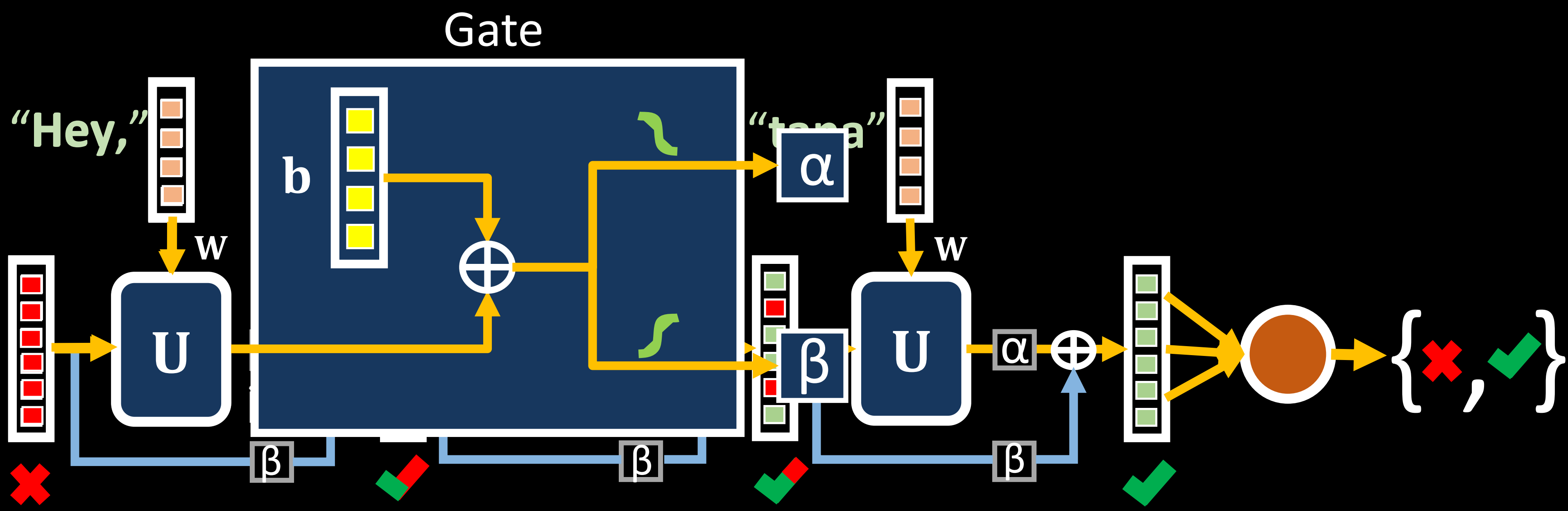


$$\boldsymbol{\beta}_t = \sigma_\beta\left(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b}_\beta\right); \widetilde{\mathbf{h}_t} = \sigma_h(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b}_h)$$

$$\boldsymbol{\alpha}_t \approx \mathbf{1} - \boldsymbol{\beta}_t; \qquad \mathbf{h}_t = \boldsymbol{\alpha}_t \odot \widetilde{\mathbf{h}_t} + \boldsymbol{\beta}_t \odot \mathbf{h}_{t-1}$$

FastGRNN

- Extend α & β from scalars to vector gates
- Accuracy: RNN ≪ Unitary RNNs < Gated RNNs ≈ FastGRNN

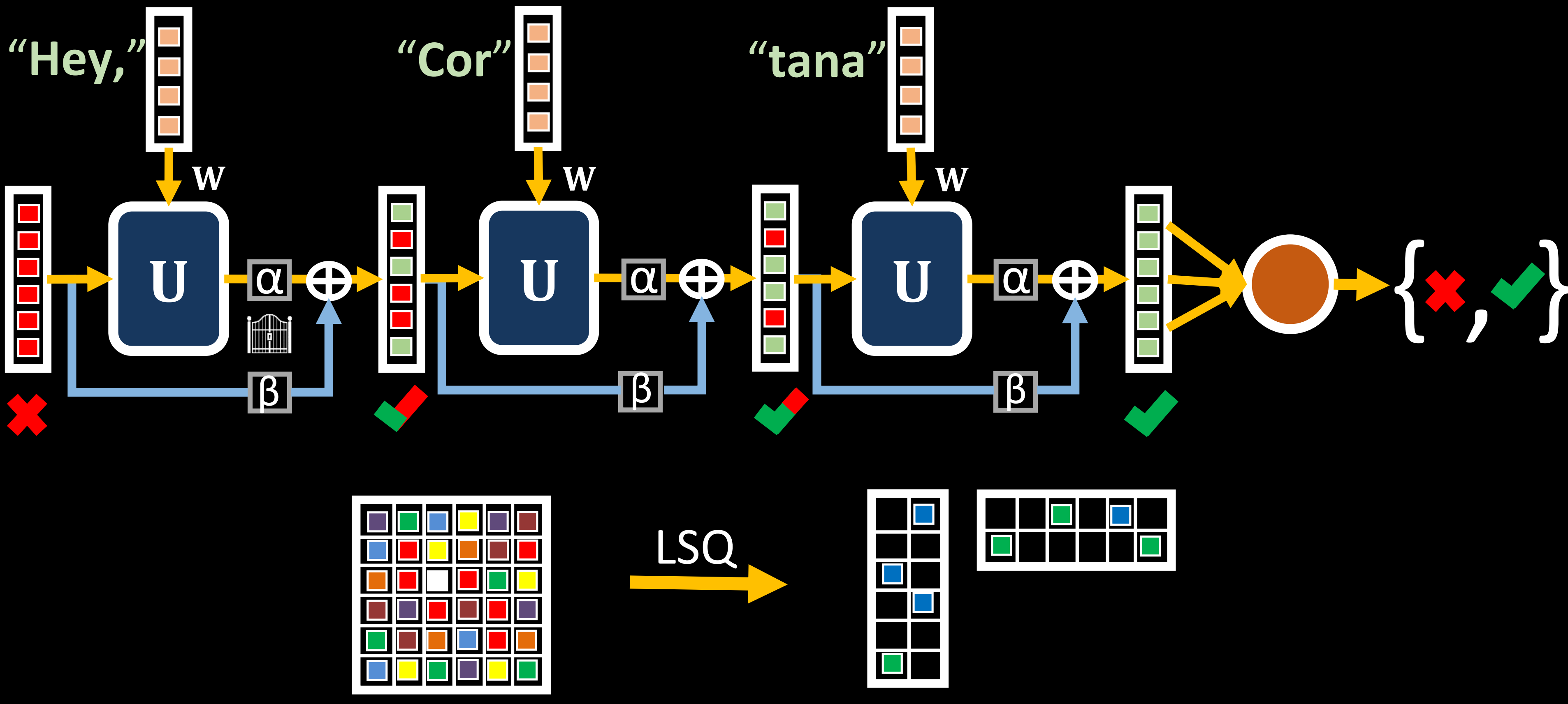


$$\boldsymbol{\beta}_t = \sigma_\beta\left(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b}_\beta\right); \widetilde{\mathbf{h}_t} = \sigma_h(\mathbf{W}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{b}_h)$$

$$\boldsymbol{\alpha}_t = \zeta(\mathbf{1} - \boldsymbol{\beta}_t) + \nu; \qquad \mathbf{h}_t = \boldsymbol{\alpha}_t \odot \widetilde{\mathbf{h}_t} + \boldsymbol{\beta}_t \odot \mathbf{h}_{t-1}$$

FastGRNN

- Make **U** and **W** low-rank (L), sparse (S) and quantized (Q)
- Model Size: FastGRNN ≪ RNN ≈ Unitary RNNs < Gated RNNs

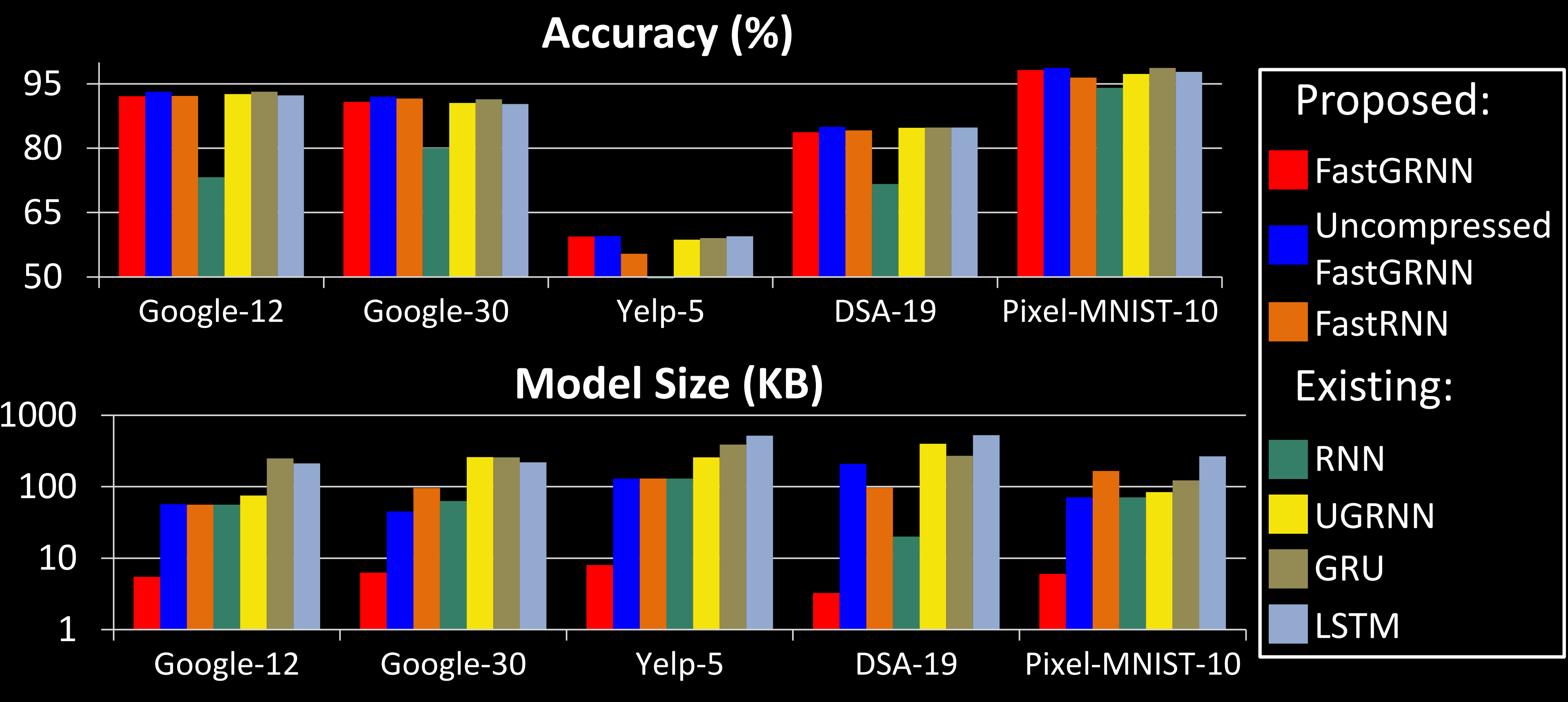


Dataset Statistics

	Dataset	# Train	# Features	# Time Steps	# Test
Speech	Google-12	22,246	3,168	99	3,081
Speech	Google-30	51,088	3,168	99	6,835
Speech	Wakeword-2	195,800	5,184	162	83,915
NLP	Yelp-5	500,000	38,400	300	500,000
NLP	PTB-10000	929,589	---	300	82,430
Activity	HAR-2	7,352	1,152	128	2,947
Activity	DSA-19	4,560	5,625	125	4,560
Image	Pixel-MNIST-10	60,000	784	784	10,000

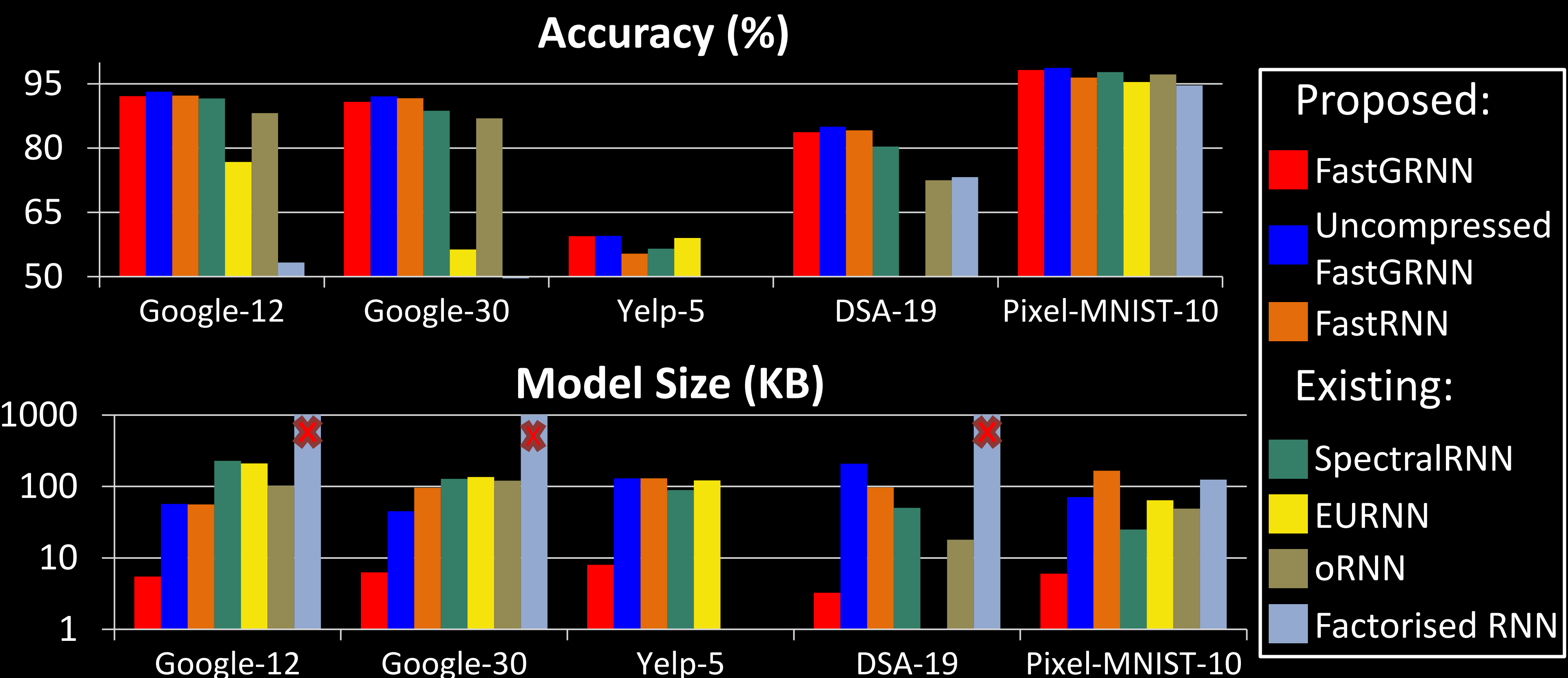
Comparison to Gated Architectures

- Uncompressed FastGRNN is as accurate as a GRU/LSTM
- FastGRNN is almost as accurate as a GRU/LSTM (within 1%)
- FastGRNN is 20-80x smaller than a GRU/LSTM



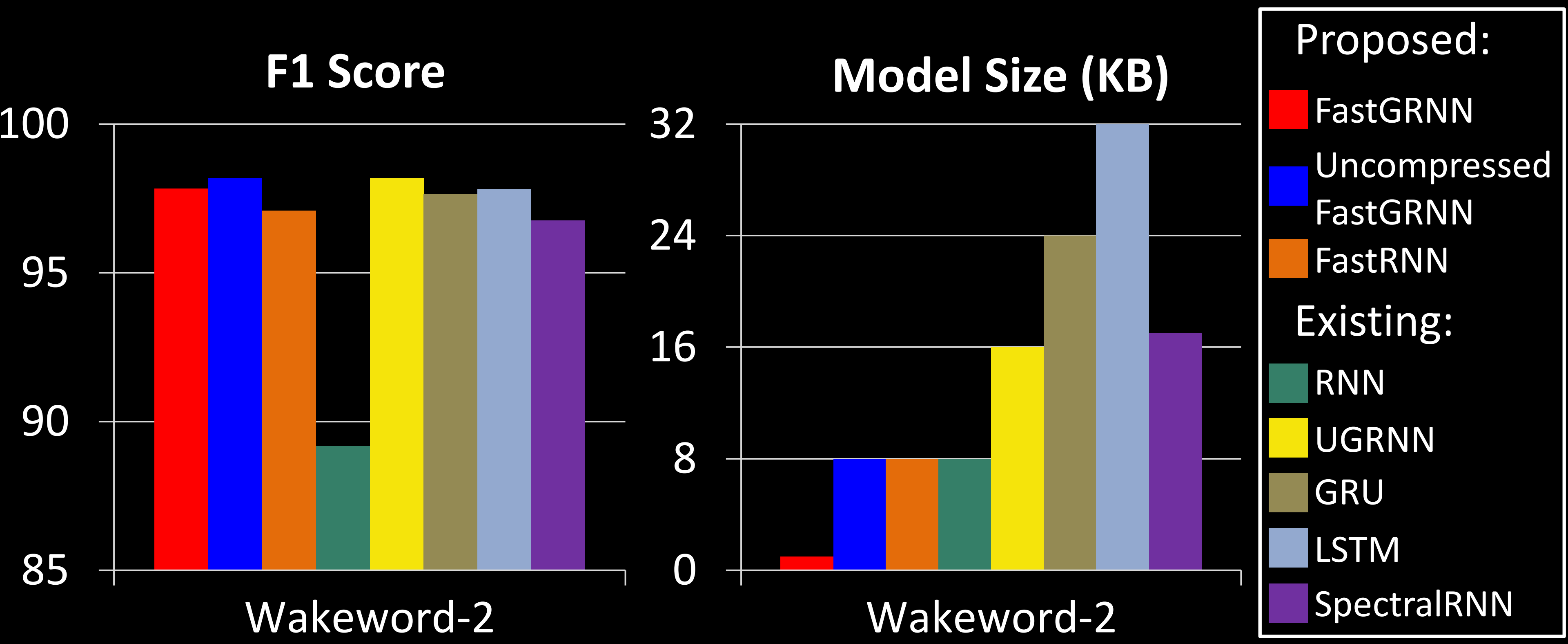
Comparison to Unitary Architectures

- FastRNN outperforms all unitary RNNs on most datasets
- FastGRNN can be 3-5% more accurate
- FastGRNN can be 45x-200x smaller



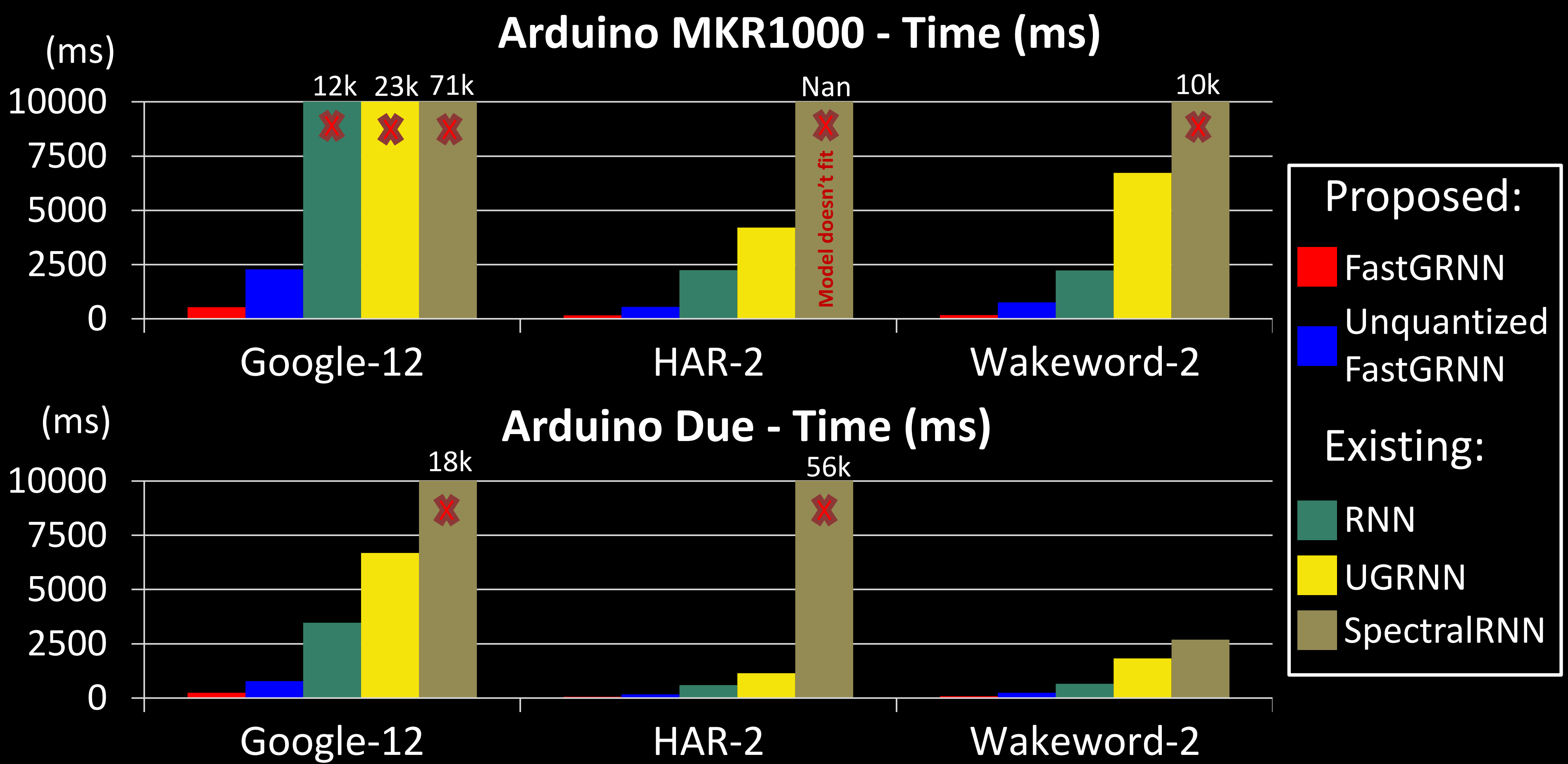
Recognizing “Hey, Cortana” in 1 KB

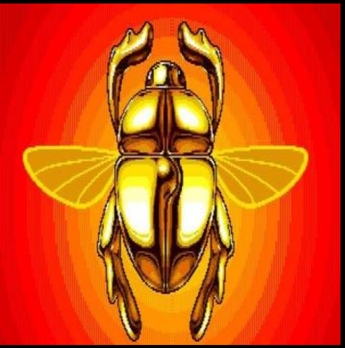
- Uncompressed FastGRNN outperforms state-of-the-art RNNs
- FastGRNN matches state-of-the-art RNN accuracies



Prediction on Edge Devices

- None of the other RNNs fit on an Arduino Uno
- FastGRNN can be 25-132x faster at prediction on the MKR1K



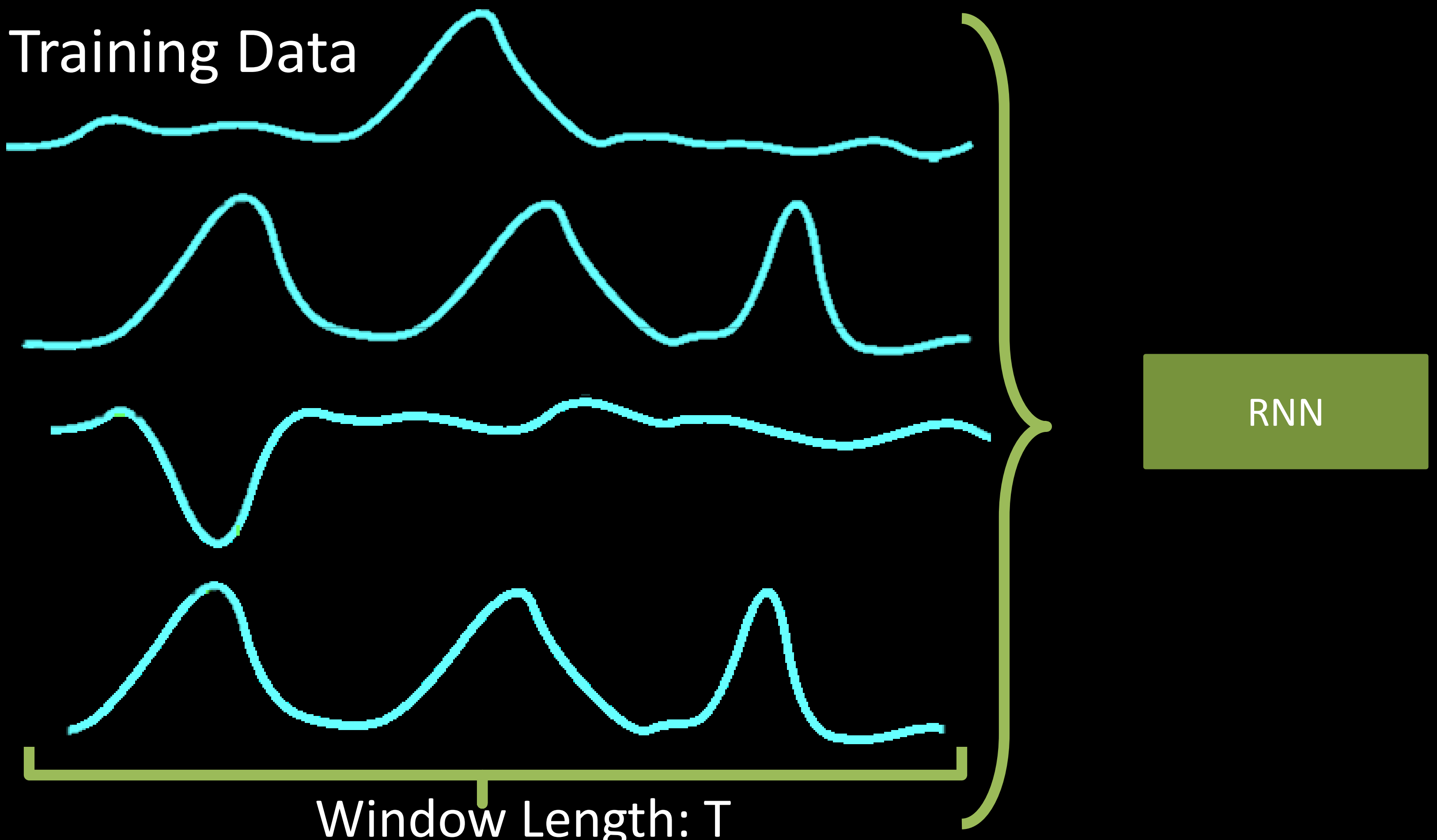



EMIRNN

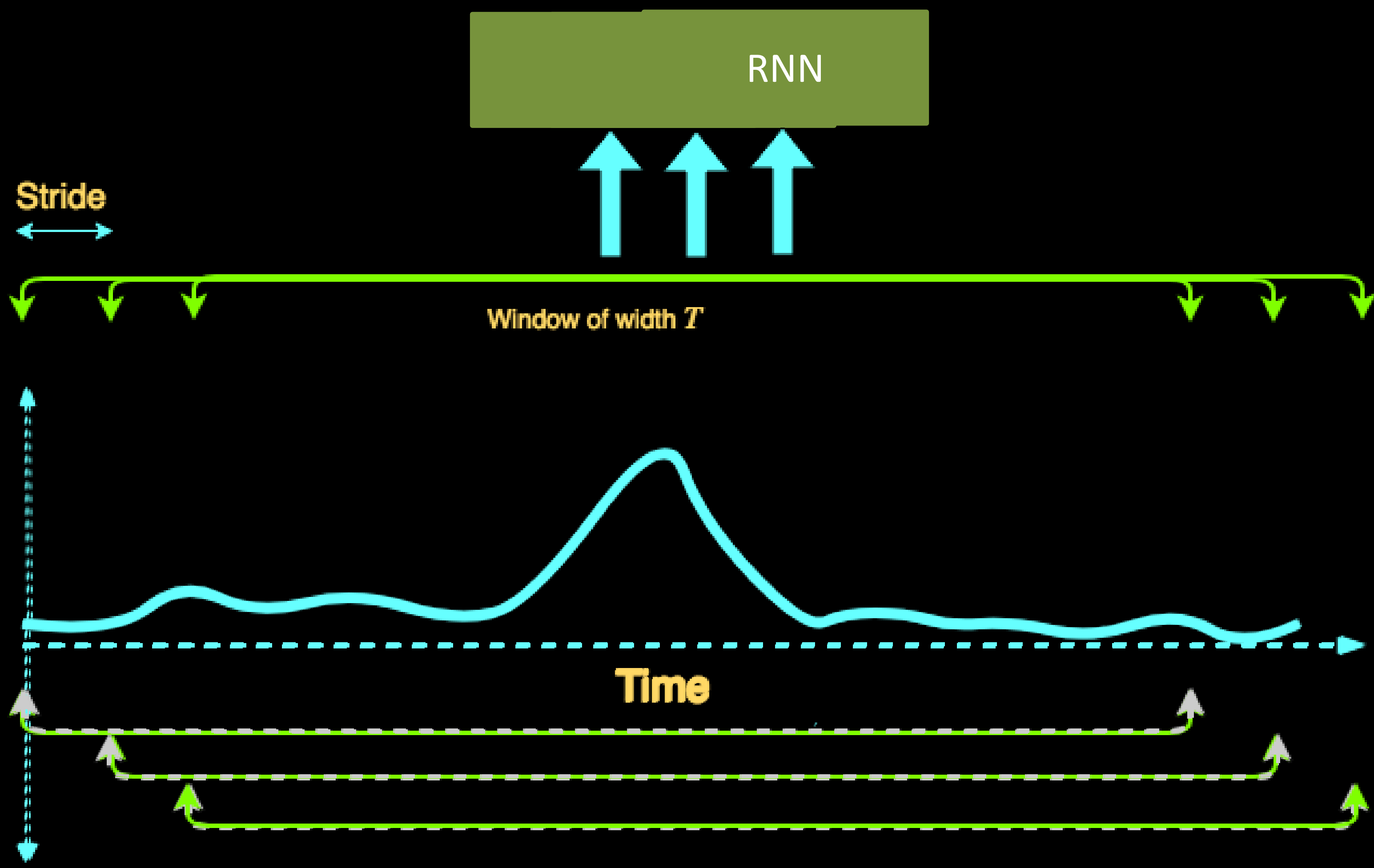
Simultaneous segmentation and early prediction in RNNs

Don Dennis (MSRI), Chirag P (MSRI), Harsha Simhadri (MSRI), P. Jain (MSRI)

Time-series Classification: Training



Time-series Analysis: Sliding Windows



Prediction Cost per Window: O(Window Size)

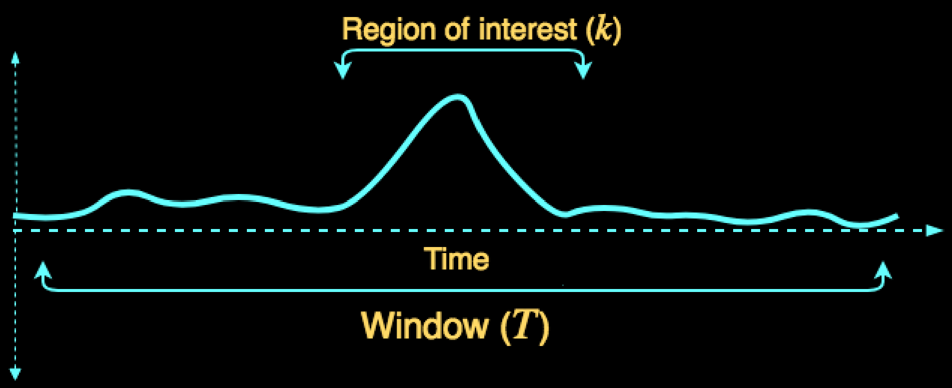
Time-series Analysis: Sliding Windows

- Complicated RNN cell updates

- Running time O(T)

- Information reuse across windows

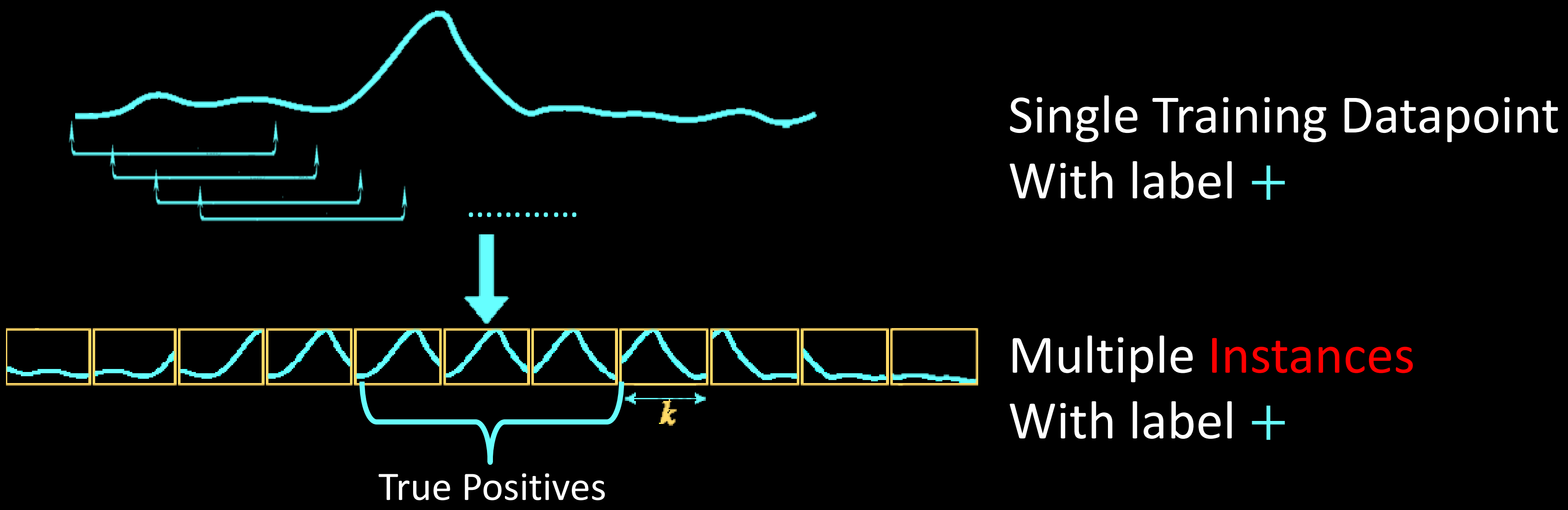
Coarse Training Data



Typically $k \ll T$, *i.e.,* actual signature of event is tiny

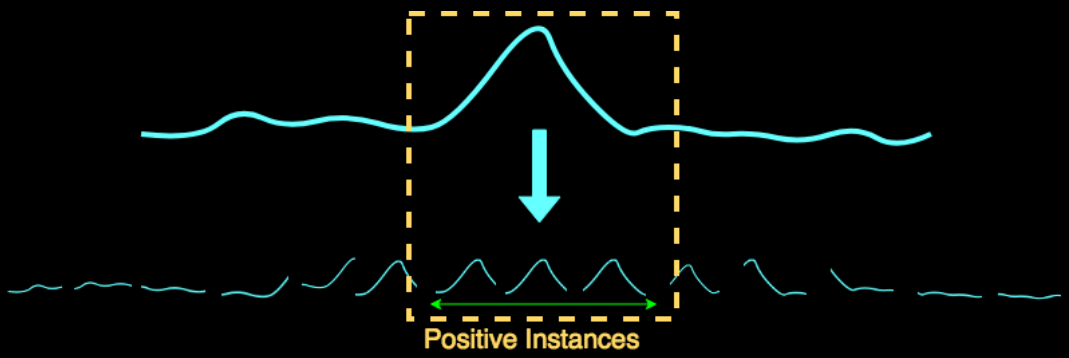
- Audio clips: 2-5secs but "Hey Cortana" typically spoken in <1sec
- *Unnecessarily large T ---* longer prediction time, lag
- Predictors must recognize signatures with different offsets - *requires larger* predictors.

Smaller Windows?



- Only a few true positives: several false positives!
- Issue: apriori location of true positives unknown

EMI-RNN: Approach

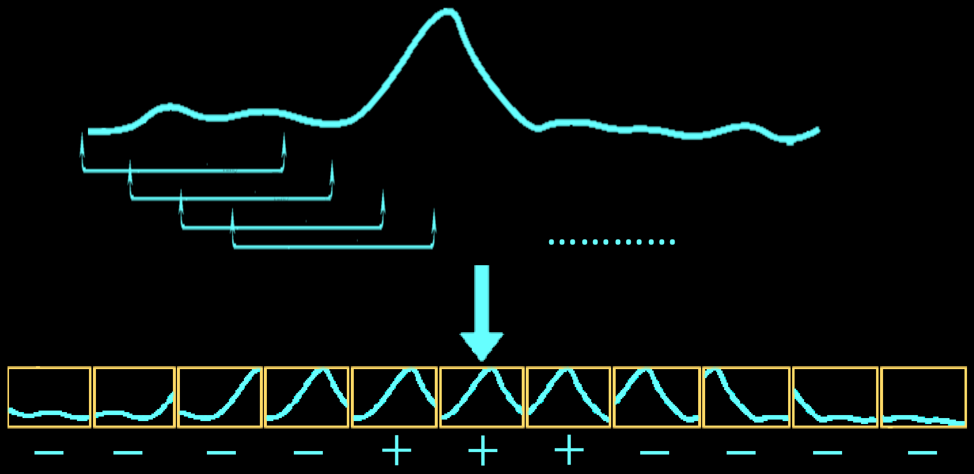


Exploit temporal locality with MIL/Robust learning techniques

Property 1: Positive instances are clustered together.

Property 2: Number of positive instances can be estimated.

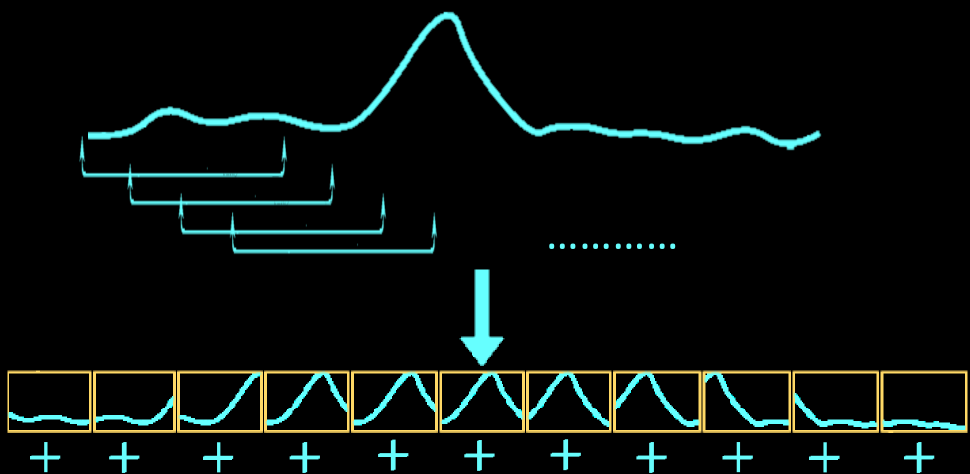
EMI-RNN: Chicken & Egg Problem



Correct Instance Labels ⟺ Accurate Prediction Model

Our Approach: be optimistic and iterate!

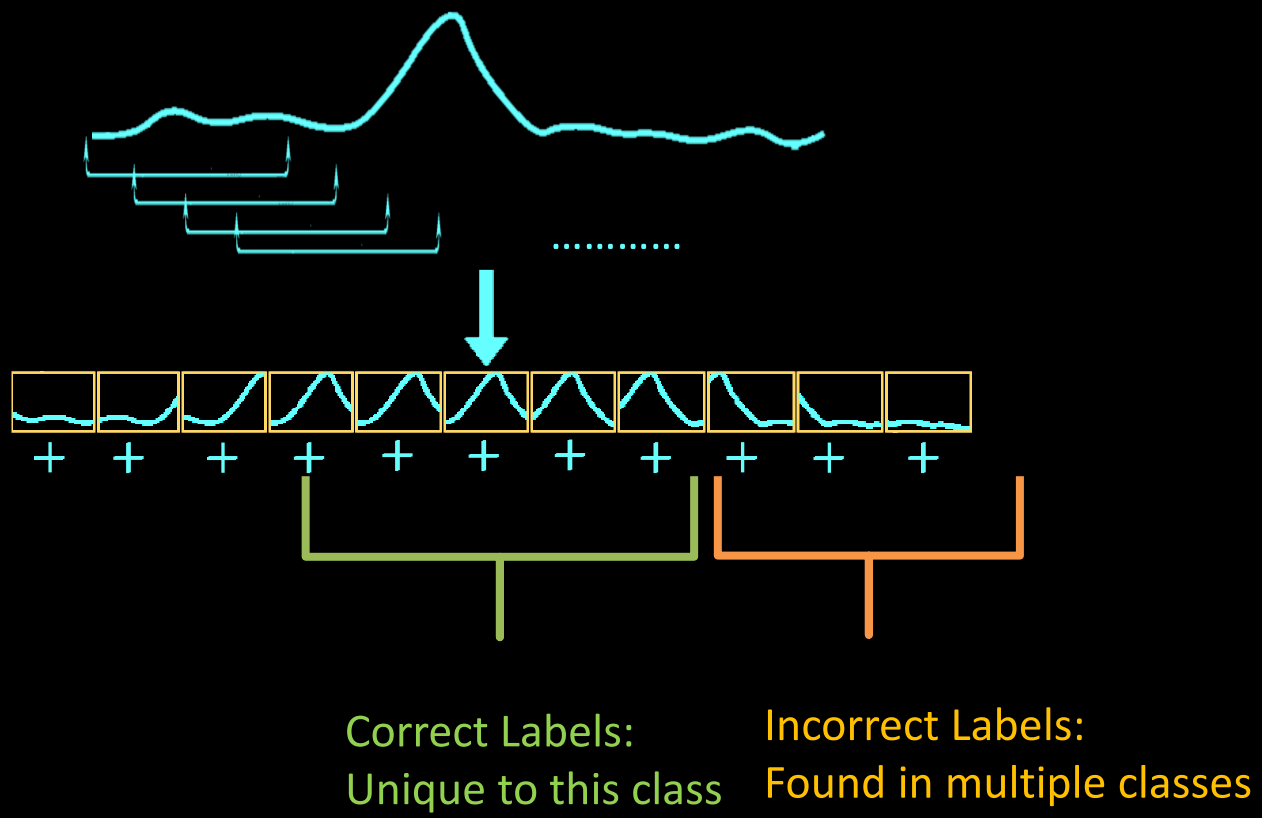
EMI-RNN: Algorithm



Estimated Instance Labels → Estimated Prediction Model

Iterate till convergence

EMI-RNN: Algorithm



EMI-RNN: Analysis?

- Optimizing:

$$\min_{W,\widehat{y_{ij}}} \sum_{i=1}^{n} \sum_{j=1}^{m} loss(\widehat{y_{ij}}, f(z_{ij}, W))$$

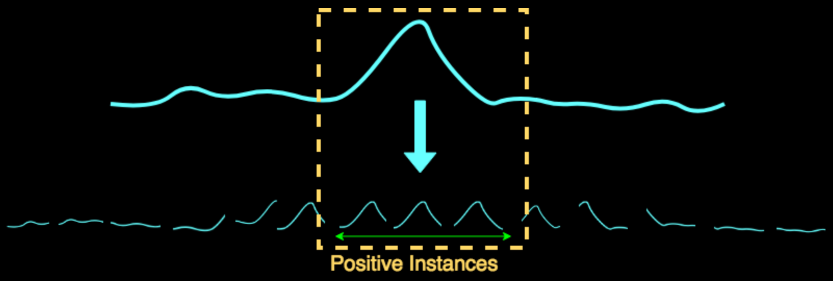
$$s.t. \sum_{j} \hat{y}_{ij} = k, \qquad i: positive$$

$$\hat{y}_{ij} \; satisfies \; temporal \; locality$$

$$\hat{y}_{ij} \in \{0,1\}, i: positive, \qquad \hat{y}_{ij} = 0, i: negative$$

- f: prediction function (LSTM/FastGRNN)
- Algorithm: alternating between $\widehat{y_{ij}}$ and W

EMI-RNN: Analysis?



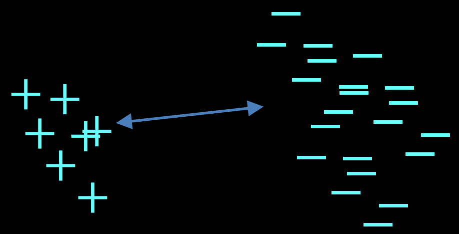
Alternating minimization for Non-convex optimization problem

- Need not converge in general!

Theorem: In $\log n$ iterations, the true positive set

$$S_* = \{(i,j), \hat{y}_{ij} = +1\}$$

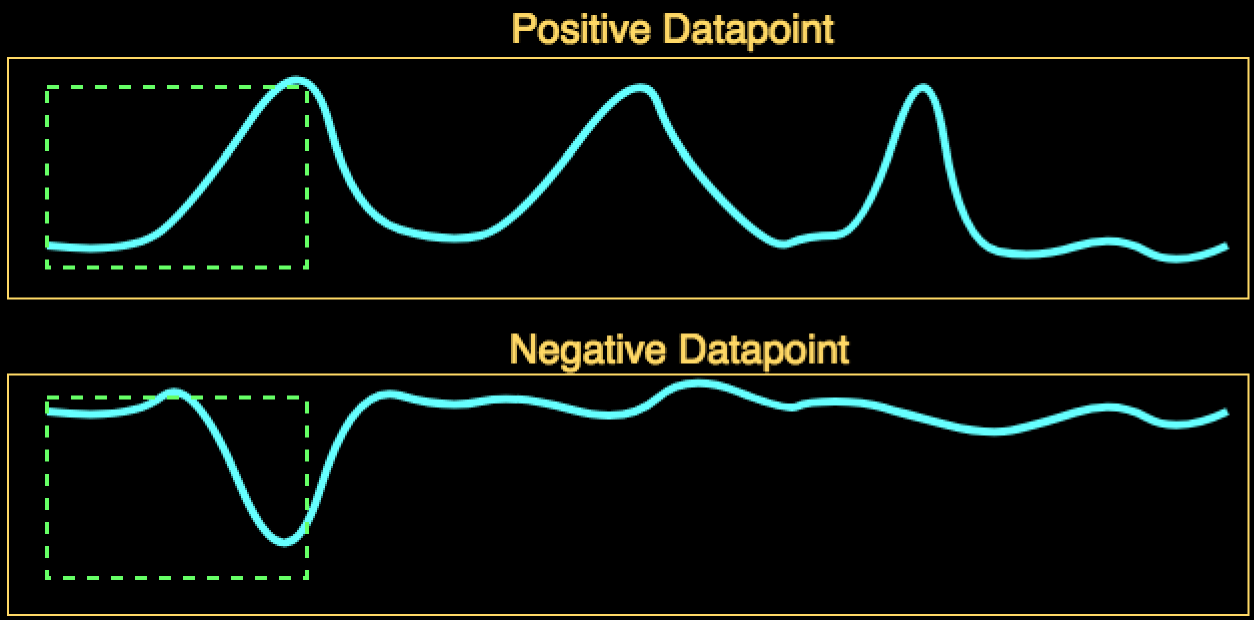
will be recovered exactly, with high probability.



Positives need not be i.i.d.

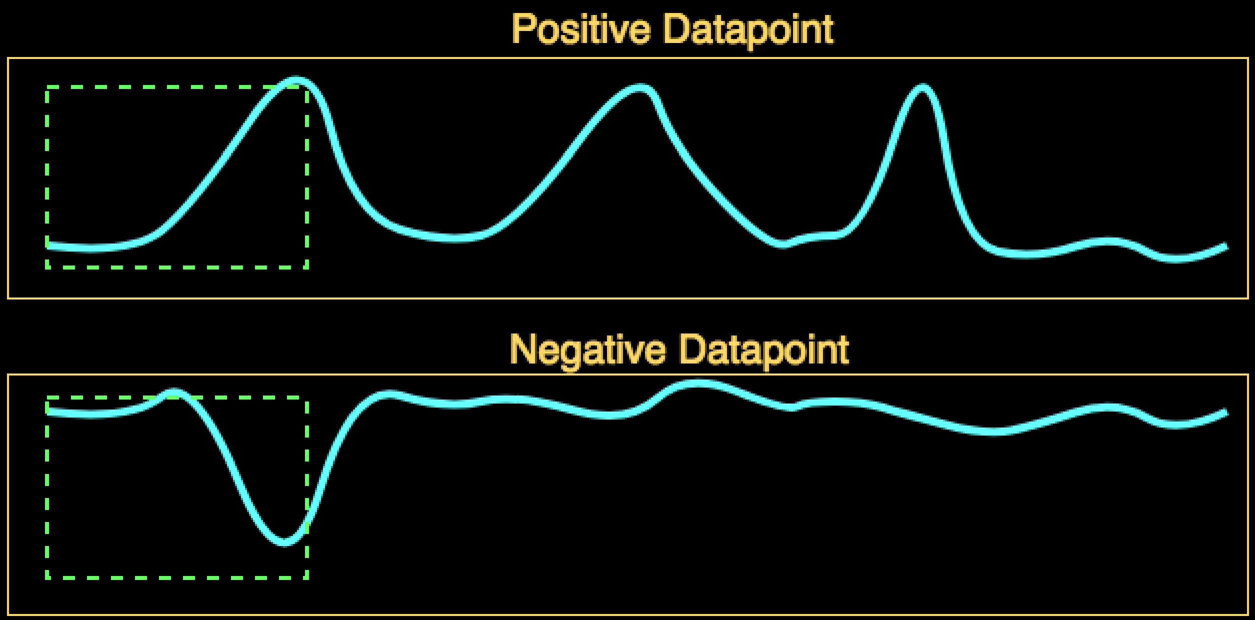
Non-homogenous setting: first such result in literature

Early Prediction?



- Existing work:
  - Assumes pretrained classifier and uses secondary classifiers
  - Template matching approaches
  - Separate policy for early classification

Early Prediction?



Our Approach

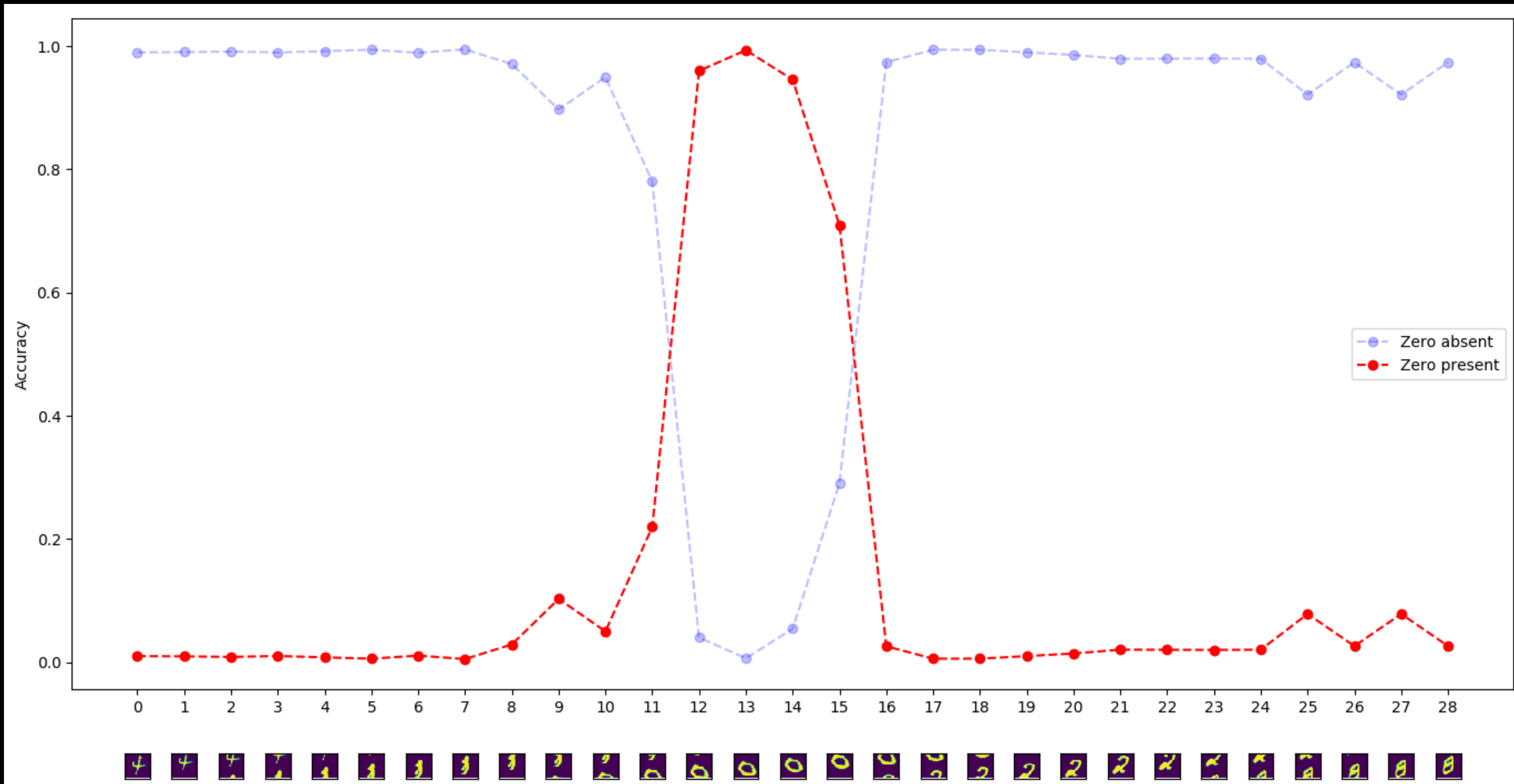
Inference: Predict at each step – stop as soon as prediction confidence is high.

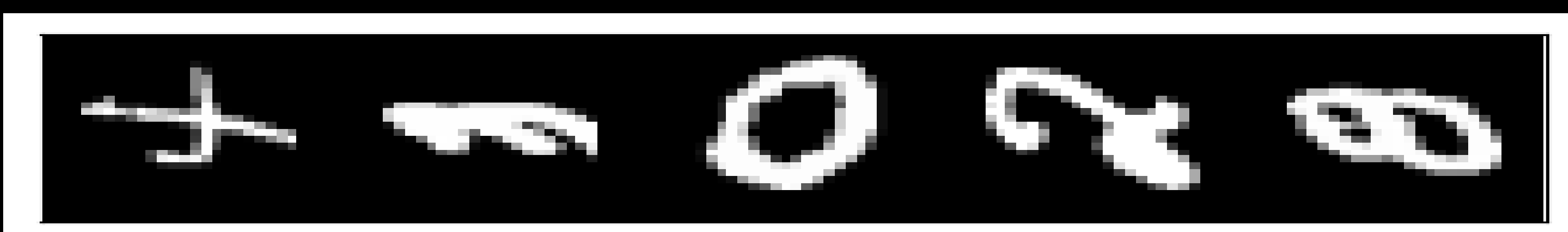
Training: Incentivize early prediction by rewarding correct and early detections.

Advantages

- Obvious: Speed
- Prediction accuracy
- Early prediction

EMI-RNN: Empirical Results





EMI-RNN: Empirical Results

Dataset	Accuracy Gain (over Baseline LSTMs)	Prediction Time Reduction
HAR	0.8%	8x
Sports	2.0%	8x
Google	1.5%	8x
Interactive Cane	1.0%	45x

EMI-RNN: Empirical Results

Dataset	Accuracy Gain (over Baseline LSTMs)	Prediction Time Reduction	Memory Savings
HAR	0.7%	11x	4x
Sports	2.0%	12x	4x
Google	1.5%	8x	4x
Interactive Cane	0.9%	72x	36x

Time-series Analysis: Conclusions

- Complicated RNN cell updates: FastGRNN
- Running time O(T): EMI-FastGRNN
- Information reuse across windows: Shallow Recurrent Networks

EdgeML repository

- Code release
  - EdgeML: 70K page views, 1017 clones, 569 stars
  - Bonsai and ProtoNN released as TLC Beta

- Used extensively in MSR India IoT Summer School
  - Automated voice feedback system
  - Radar-based poacher detection and SONYC
  - Predictive maintenance for solar panels

- https://github.com/Microsoft/EdgeML

Thank You