Neural Speed Reading via Skim-RNN

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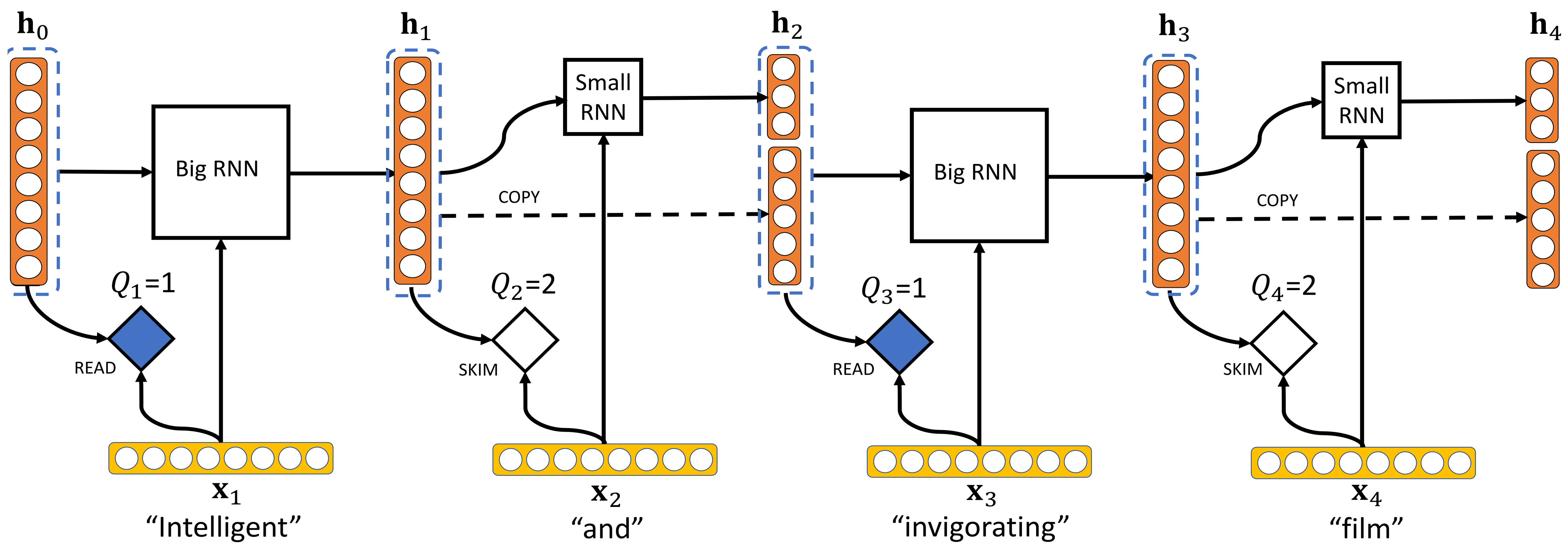


Motivation

RNN on CPUs

- RNNs are slow on CPUs/GPUs
- CPUs are often more desirable than GPUs

Human Speed Reading

- **Skim** unimportant words and **fully read** important words

Our contributions

- Dynamically decide which one to use between big and small RNN with shared hidden state
- Same interface as standard RNN → Easily Replaceable
- Computational Advantage over standard RNN on CPUs with comparable/better accuracy

Model

Consists of two RNNs, sharing hidden state

- **Big RNN** (hidden size of d)
  updates the entire hidden state. O(d²)
- **Small RNN** (hidden size of d', where d≫d')
  updates a small portion of the hidden state. O(d'd)

x_t: Input state at t,
h_t: Hidden state at t,
Q_t: Random variable for skim decision at t

$$p_t = \text{softmax}(\alpha(x_t, h_{t-1}))$$
$$Q_t \sim \text{Multinomial}(p_t)$$

$$h_t = \begin{cases} f(x_t, h_{t-1}), & \text{if } Q_t = 1 \\ [f'(x_t, h_{t-1});\ h_{t-1}[d'+1:d]], & \text{if } Q_t = 2 \end{cases}$$

(f, f': big and small RNN, respectively)

Training

$$L'(\theta; Q) = L(\theta; Q) + \gamma \frac{1}{T}\sum_{t=1}^{T}(-\log(\Pr[Q_t = 2]))$$

(γ: hyperparameter, encourages skimming)

Goal: minimize $\mathbb{E}[L'(\theta)] = \sum_Q L'(\theta; Q)\Pr(Q)$
→ sample space = 2^T for $Q = [Q_1, \ldots, Q_T]$

Gumbel-Softmax

- Biased but low variance, good empirical results
- Reparameterize $h_t = r_t^1 h_t^1 + r_t^2 h_t^2$, where
  $$r_t^i = \frac{\exp((\log(p_t^i) + g_t^i)/\tau)}{\sum_j \exp((\log(p_t^j) + g_t^j)/\tau)}$$
  $$(g \sim \text{Gumbel}(0,1), \tau: \text{hyperparameter})$$
- Slowly anneal (decrease τ), making the distribution more discrete to allow differentiation with stochasticity

Related Work

LSTM-Jump (Yu et al., 2017)

- Skip rather than skim
- No outputs for skipped time steps

Variable-Computation RNN (VCRNN) (Jernite et al., 2017)

- Use 1 RNN, and controls # of hidden units to update by making a d-way decision
- Required to be invariant of # of hidden units being updated
- Computing loss is more intractable (d^T vs 2^T)

Experiments

Text Classification (w/ LSTM)

Dataset	SST	Rotten Tomatoes	IMDb	AGNews
Regular	86.4	82.5	91.1	93.5
LSTM-Jump	-	79.3 / 1.6x Sp	89.4 / 1.6x Sp	89.3 / 1.1x Sp
VCRNN	81.9 / 2.6x FLOP-R	81.4 / 1.6x Sp	-	-
Skim-RNN	**86.4 / 3.0x** FLOP-R	**84.2 / 1.3x** Sp	**91.2 / 2.3x** Sp	**93.6 / 1.0x** Sp

▲ Accuracy, Floating point operation reduction (FLOP-R) and Speed-up (Sp). Skim-RNN achieves comparable to/better than regular RNN and related work, with up to 3.0x FLOP-R.

Question Answering (SQuAD) (w/ LSTM+Attention)

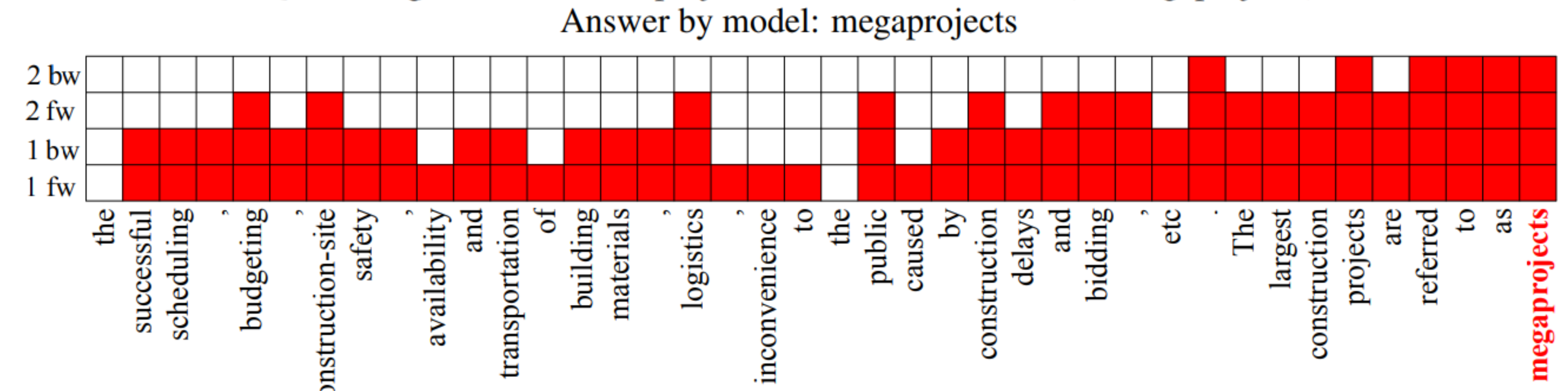
	F1	Exact Match	FLOP-R
Regular	75.5	67.0	1.0x
VCRNN	74.9	65.4	1.0x
Skim-RNN	**75.0**	**66.0**	**2.3x**

▲ Skim-RNN achieves comparable result to Regular RNN with 2.3x FLOP-R on SQuAD.

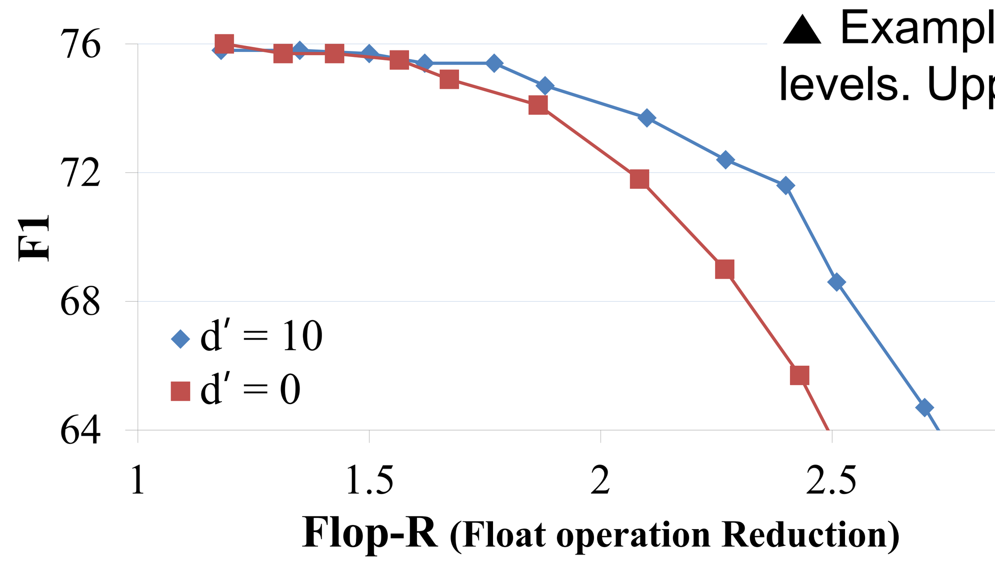
Positive	I **liked** this movie, not because Tom Selleck was in it, but **because** it was a **good** story about baseball and it also had a semi-over **dramatized** view of some of the issues that a BASEBALL player coming to the end of their time in Major League sports must face. I also **greatly enjoyed** the cultural differences in American and Japanese baseball and the small facts on how the games are played differently. **Overall**, it is a **good movie** to watch on Cable TV or rent on a cold winter's night and watch about the "Dog Day's" of summer and know that spring training is only a few months away. A **good** movie for a baseball fan as well as a good "DATE" movie. Trust me on that one! *Wink*
Negative	**No**! **no** - **No** - **NO**! My **entire** being is **revolting** against this **dreadful** remake of a classic movie. I **knew** we were heading for trouble from the moment Meg Ryan appeared on screen with her **ridiculous** hair and clothing - literally looking like a scarecrow in that garden she was digging. Meg Ryan playing Meg Ryan - how **tiresome** is that?! And it **got worse** ... so much **worse**. The **horribly cliché** lines, the stock characters, the increasing sense I was **watching** a spin-off of "The First Wives Club" and the ultimate **hackneyed** schtick in the delivery room. How many times have I seen this movie? Only once, but it **feel** like a dozen times - **nothing** original or fresh about it. For shame!

▲ Examples on IMDb. Skim-RNN skims **black words** and fully reads **blue words**.

Q: The largest construction projects are known as what? (A: megaprojects)
Answer by model: megaprojects



▲ Examples on SQuAD with Skim-RNNs in different levels. Upper LSTMs skim more than lower LSTMs do.



◀ Trade-off between F1 and FLOP-R, obtained by adjusting the threshold for the skim. d'=10 & d'=0.