

Wyprawa w głąb LSTMa

CORE, 13 maja 2020
Julia Bazińska

Na podstawie Greff et al., LSTM: A Search Space Odyssey

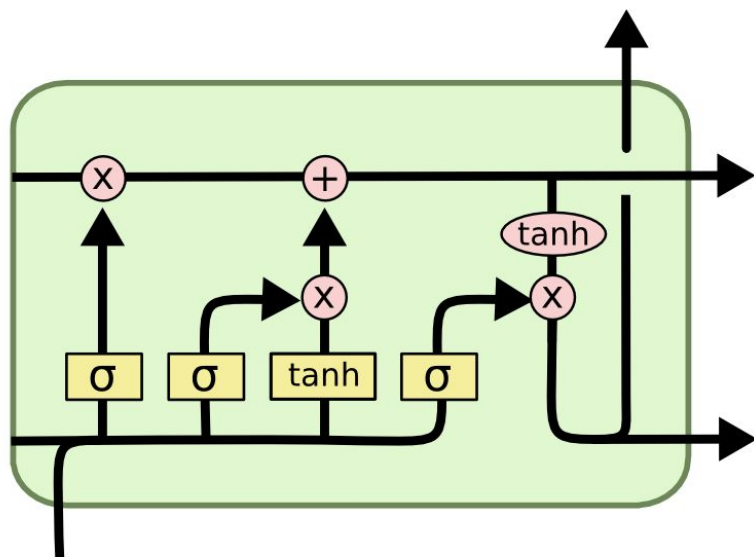
Long Short-Term Memory

“Recurrent networks can in principle use their feedback connections to store representations of recent input events in the form of activations ("short-term memory", as opposed to "long-term memory embodied by slowly changing weights).”

Hochreiter et al, “Long Short-Term Memory”, 1997

Agenda

1. LSTM vs prosta jednostka
2. Co tam się właściwie dzieje?
Szczegóły działania.
3. Możliwe warianty
4. Trzy benchmarki
5. Wyniki



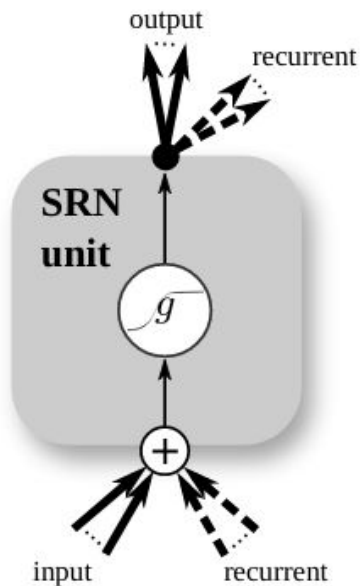


nope



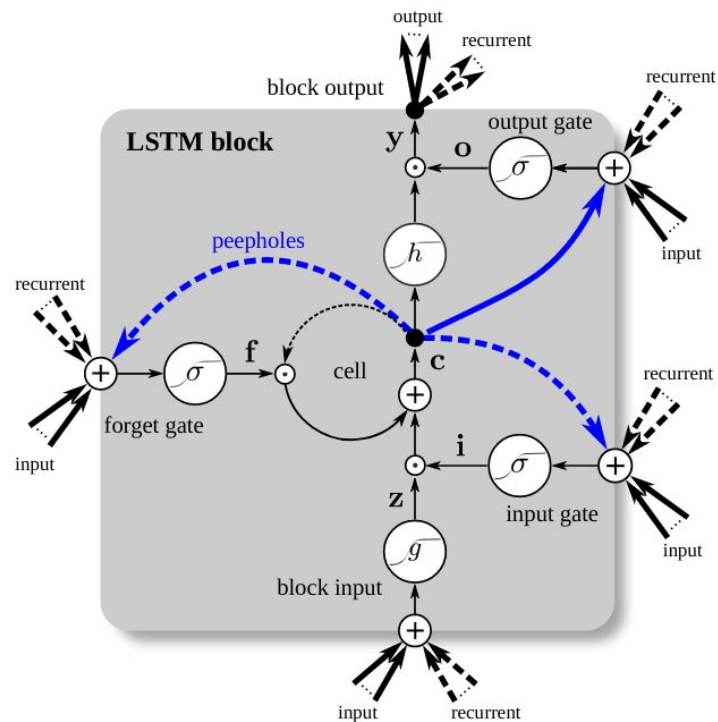
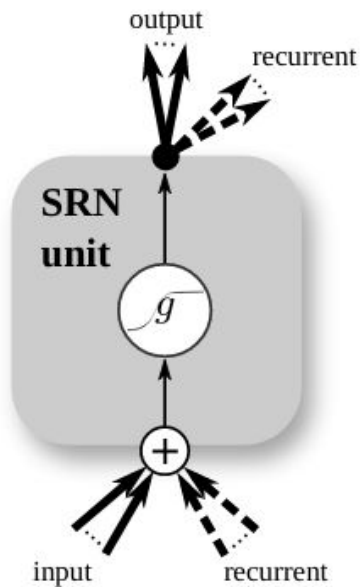
LSTM vs prosta jednostka rekurencyjna

Najprostsza jednostka rekurencyjna

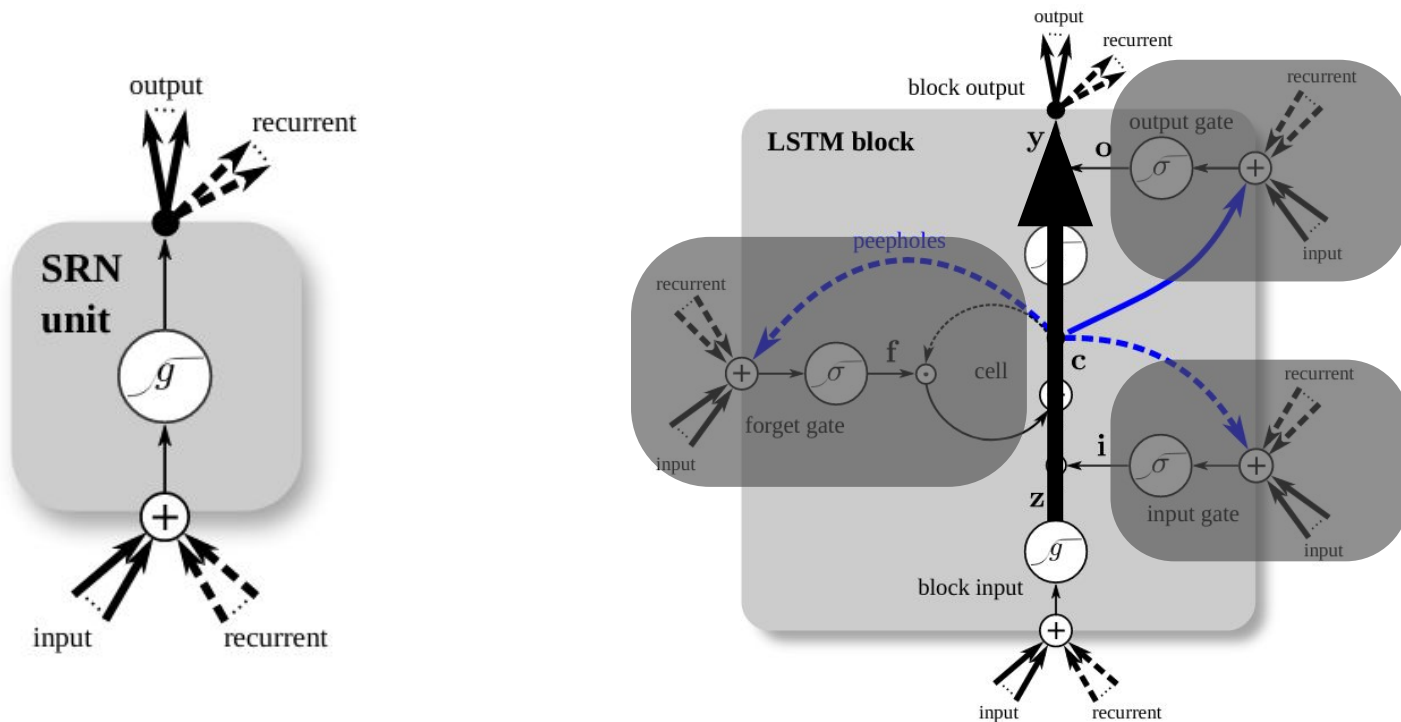


$$y_t = g(W x_t + R y_{t-1} + b)$$

...kontra LSTM

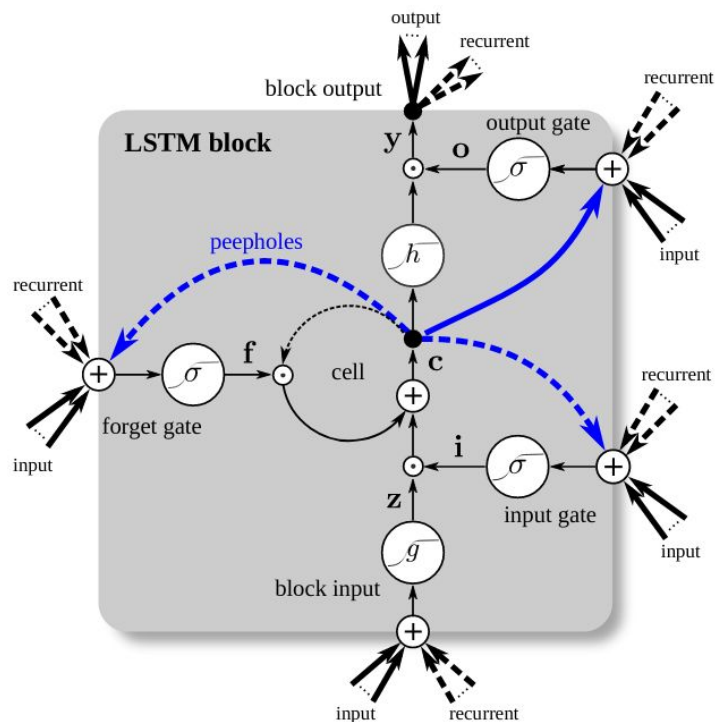


Czy to na pewno jest potrzebne?



Co tam się właściwie
dzieje?

Co tam się właściwie dzieje?



$$\bar{z}^t = W_z x^t + R_z y^{t-1} + b_z$$

$$z^t = g(\bar{z}^t)$$

block input

$$\bar{i}^t = W_i x^t + R_i y^{t-1} + p_i \odot c^{t-1} + b_i$$

$$i^t = \sigma(\bar{i}^t)$$

input gate

$$\bar{f}^t = W_f x^t + R_f y^{t-1} + p_f \odot c^{t-1} + b_f$$

$$f^t = \sigma(\bar{f}^t)$$

forget gate

$$c^t = z^t \odot i^t + c^{t-1} \odot f^t$$

cell

$$\bar{o}^t = W_o x^t + R_o y^{t-1} + p_o \odot c^t + b_o$$

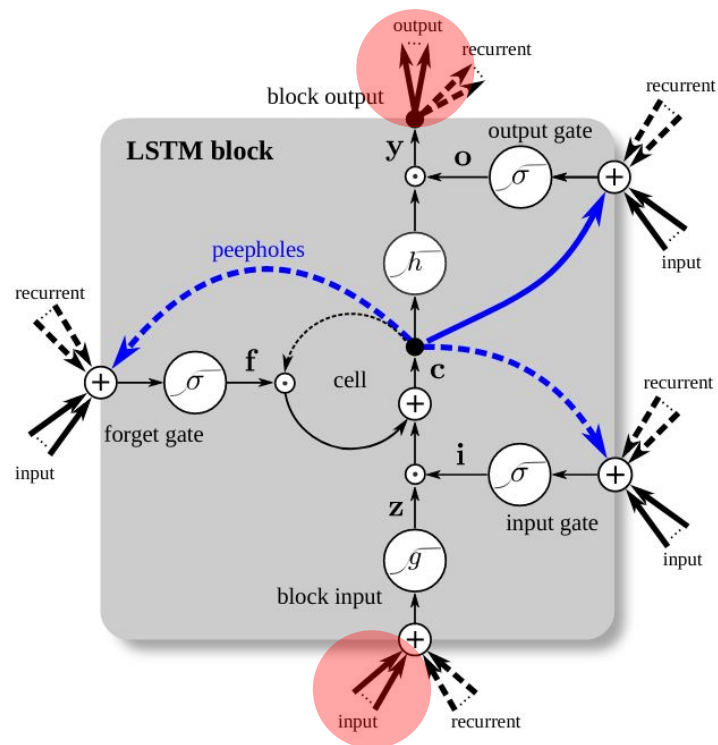
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$$y^t = h(c^t) \odot o^t$$

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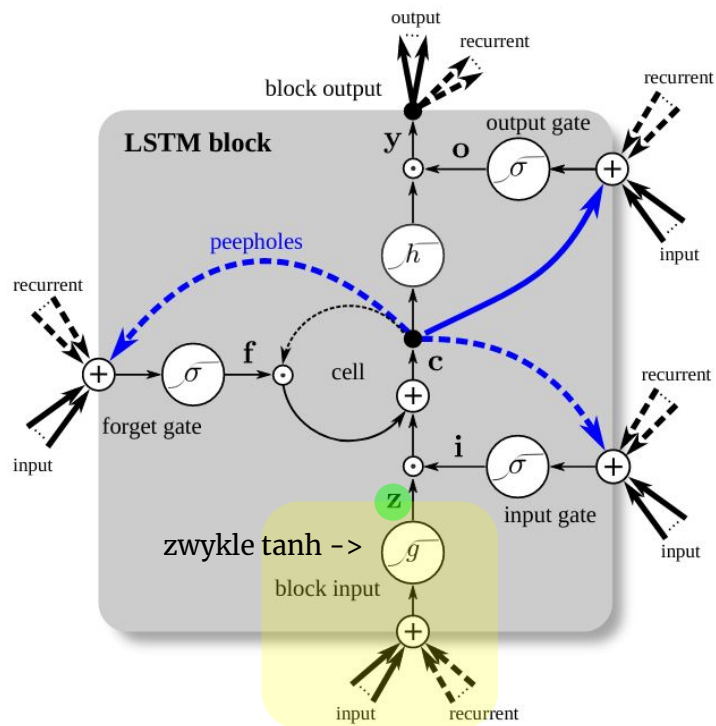
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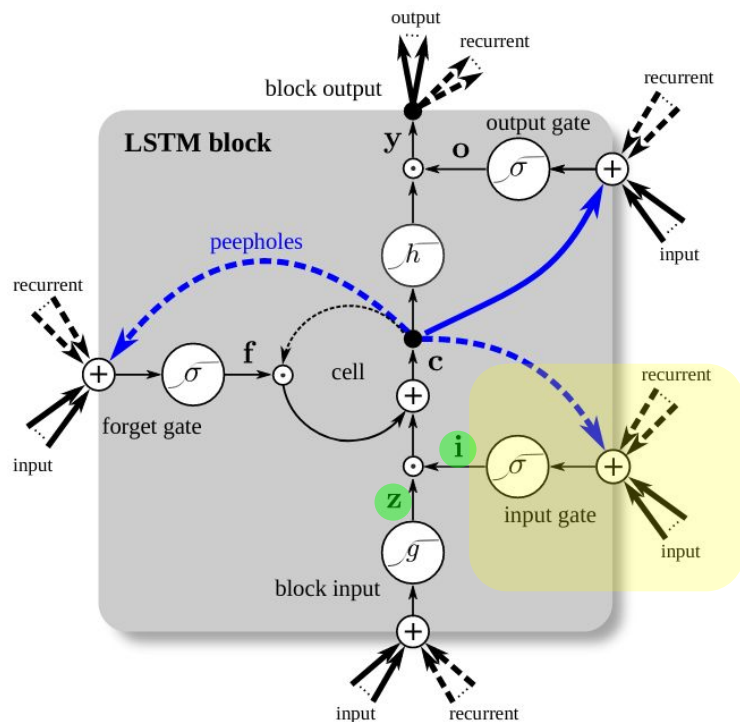
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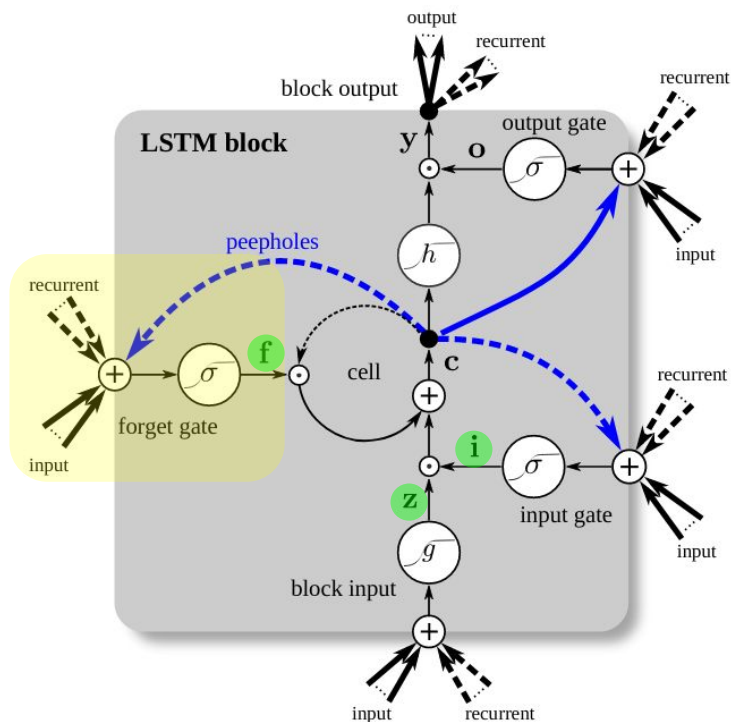
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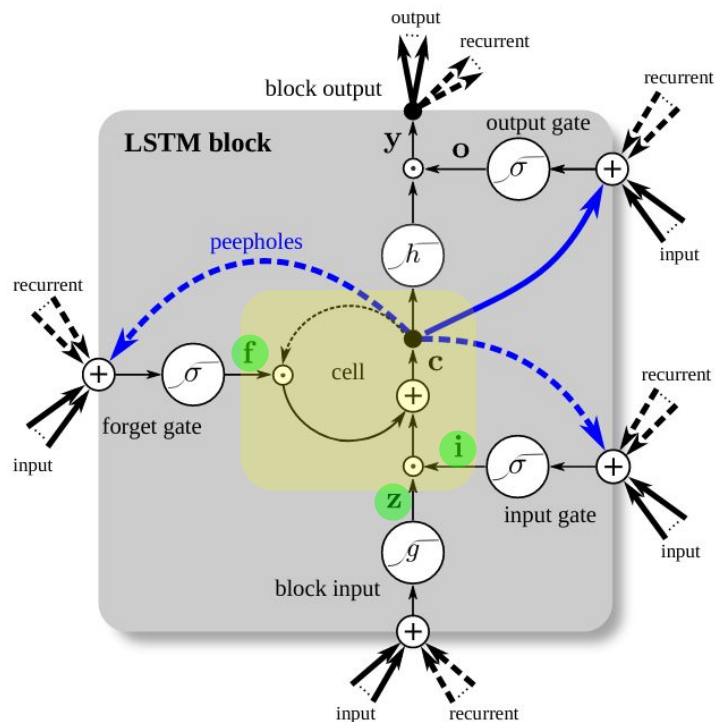
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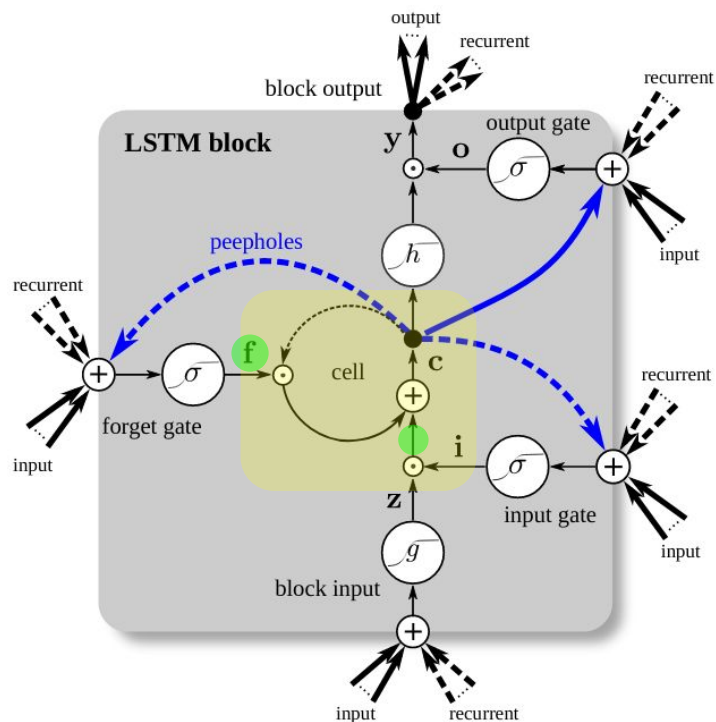
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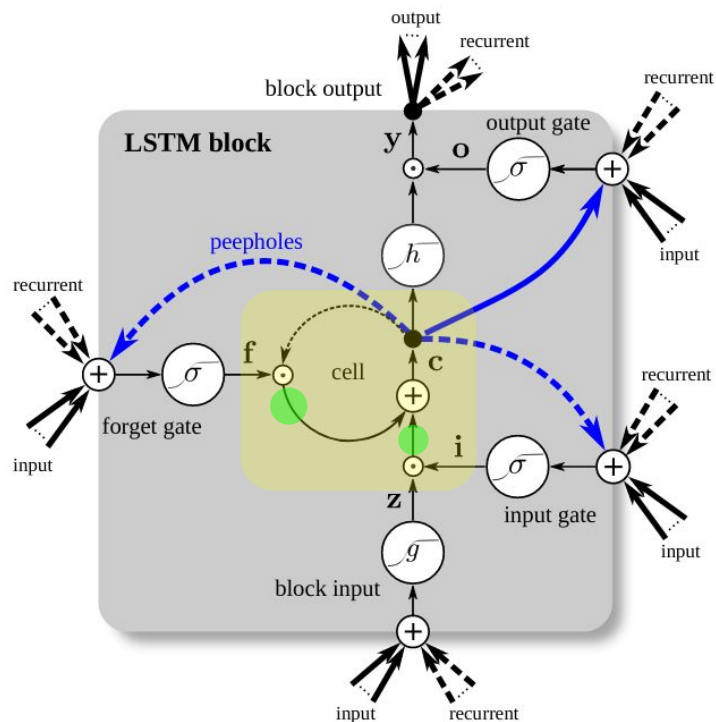
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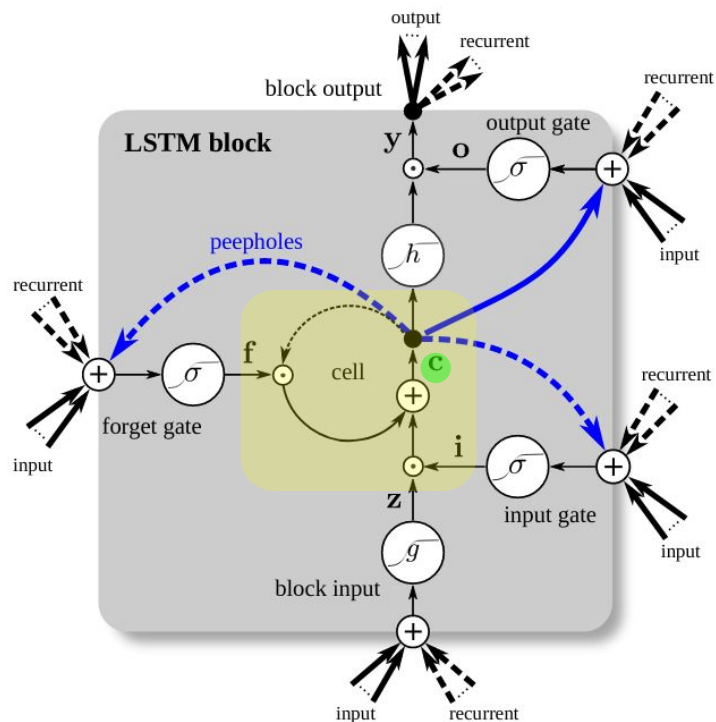
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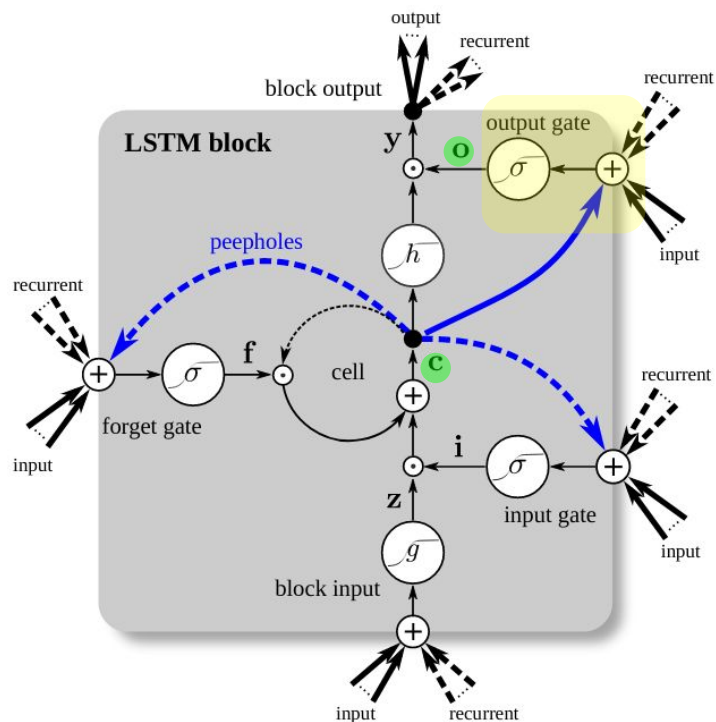
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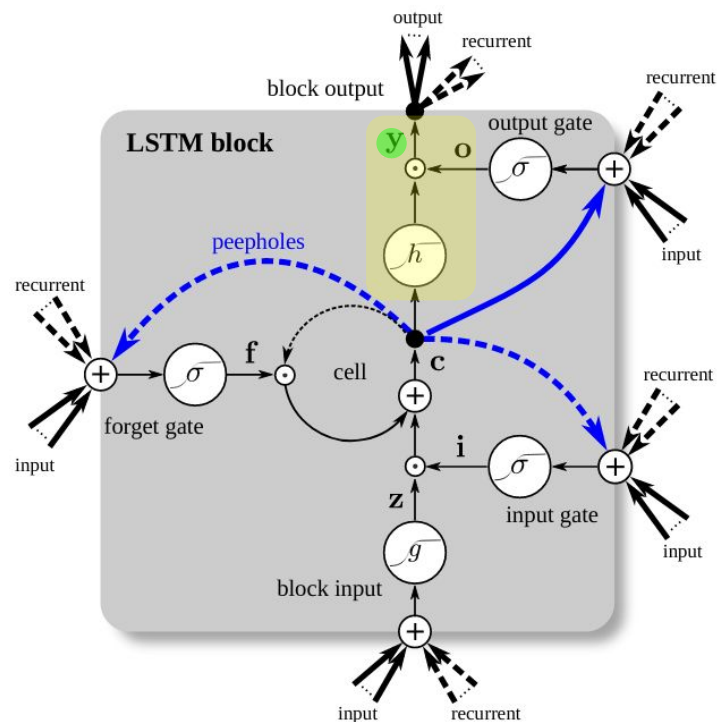
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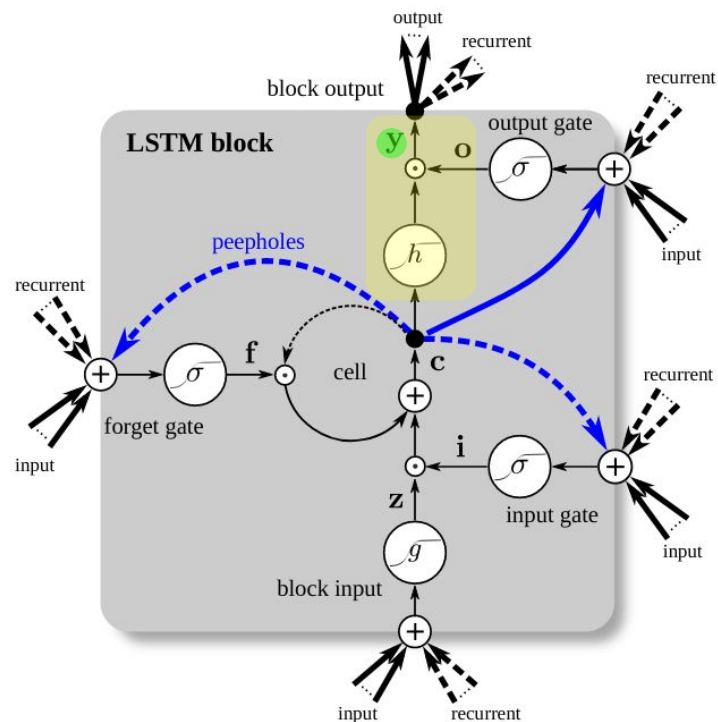
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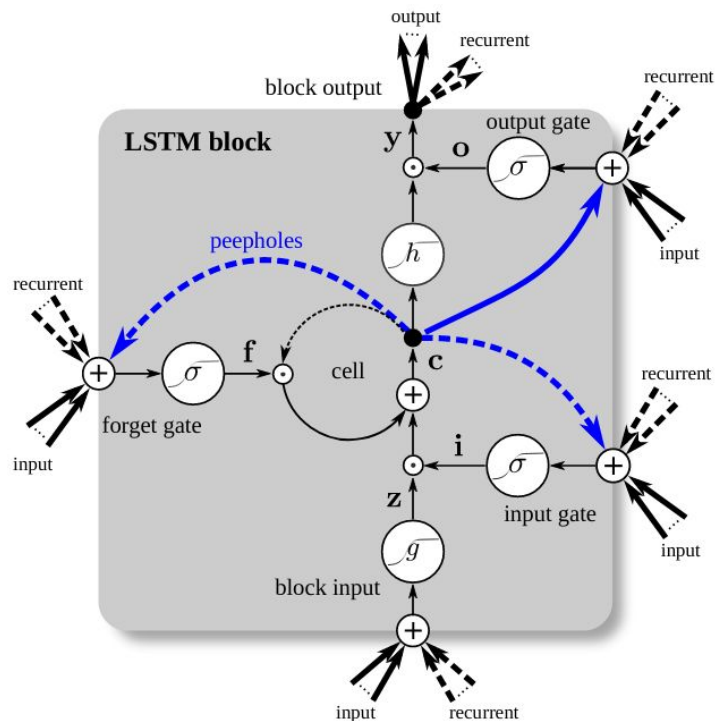
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block output

Peephole connections



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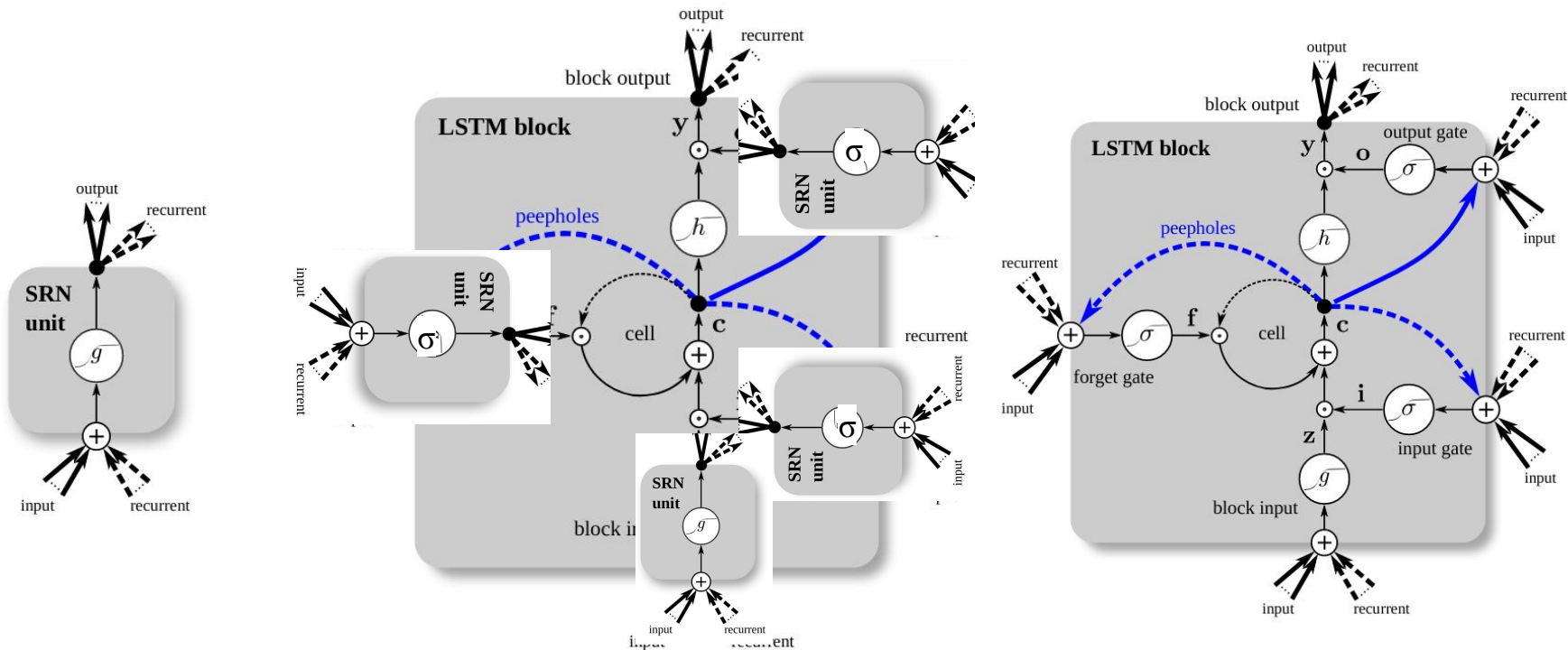
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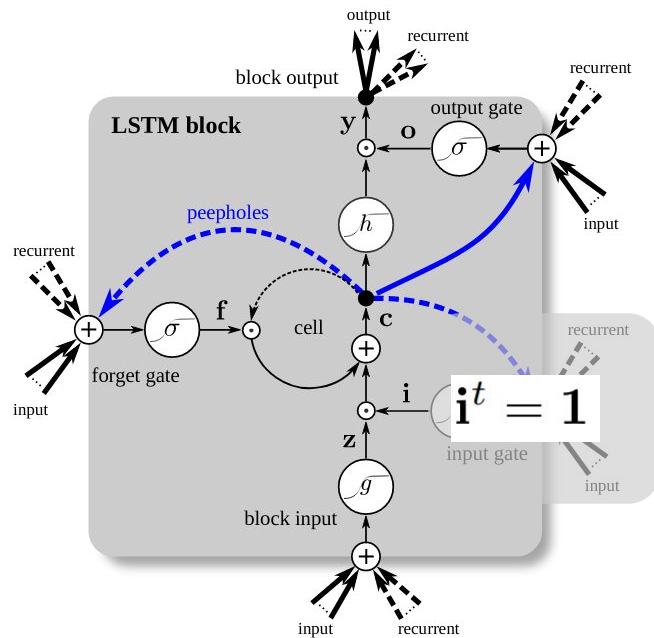
LSTM vs prosta jednostka reukrencyjna



Warianty LSTM

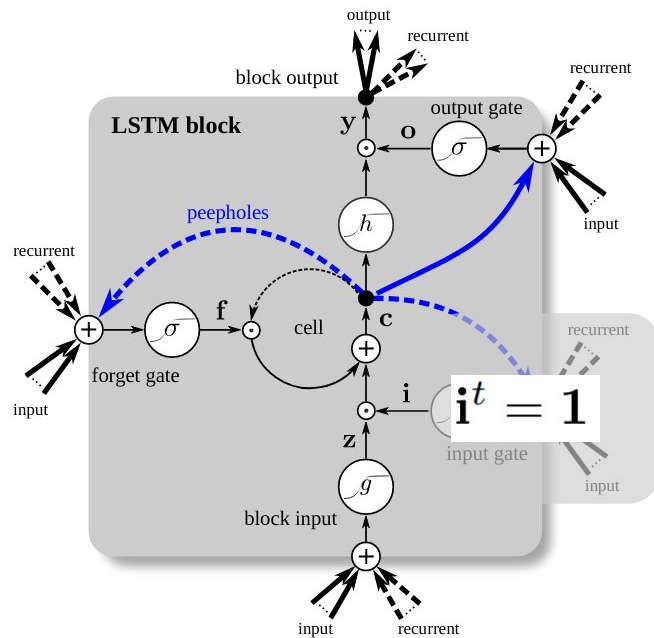
Warianty

1. Usunięcie gate'a:
 - a. No Input Gate
 - b. No Forget Gate
 - c. No Output Gate
2. Usunięcie aktywacji:
 - a. No Input Activation Function
 - b. No Output Activation Function
3. Couple Input and Forget Gate
4. No Peepholes
5. Full Gate Recurrence



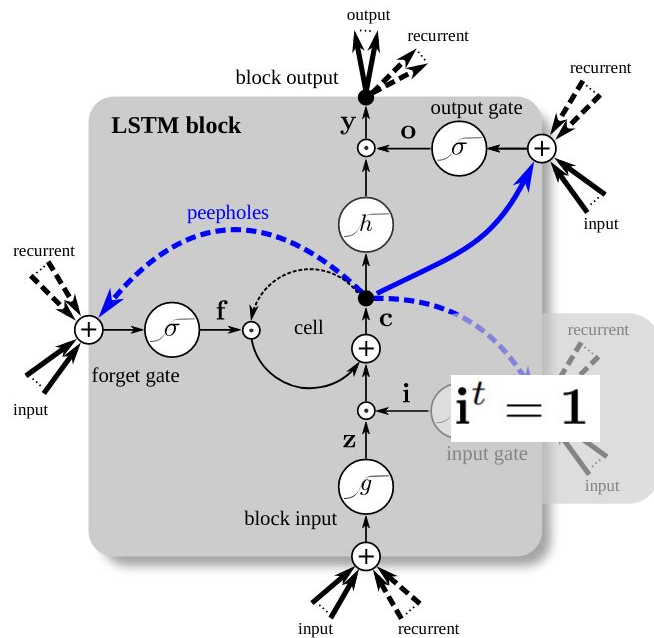
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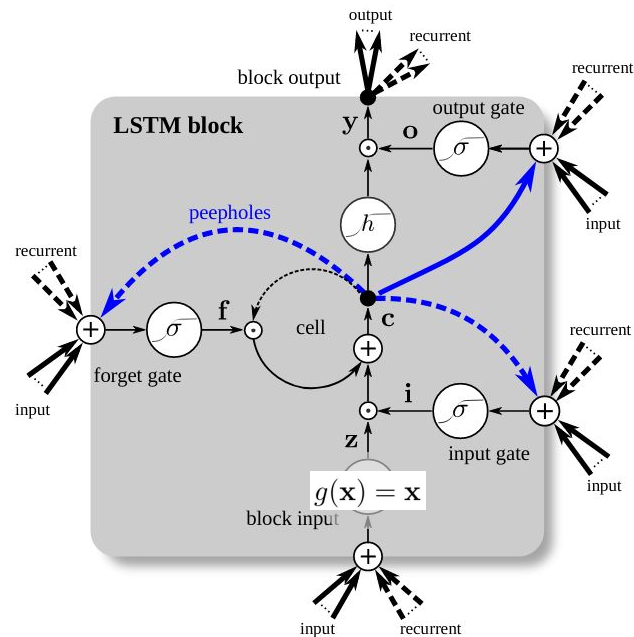
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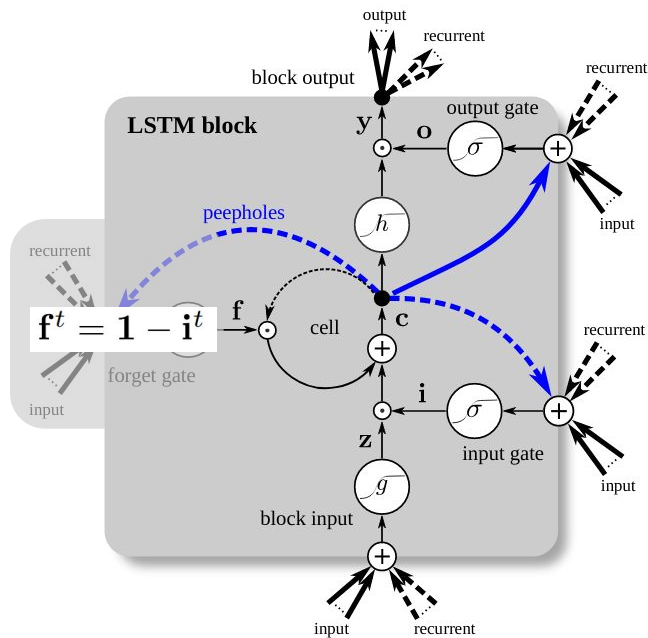
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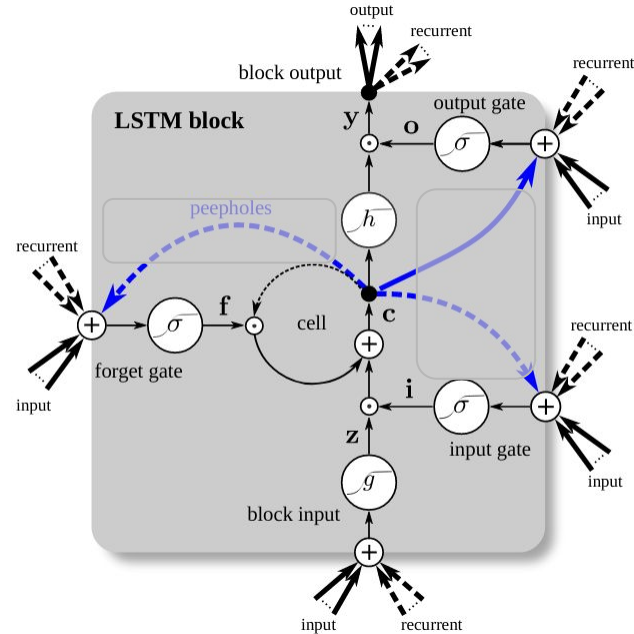
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3. **Coupled Input and Forget Gate**
4. No Peepholes
5. Full Gate Recurrence



Warianty

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3. Coupled Input and Forget Gate
4. No Peepholes
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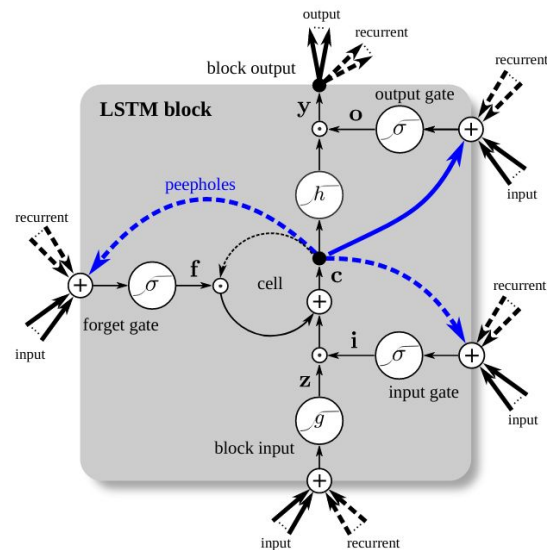


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każdy gate + wyniki z poprzedniego kroku ze wszystkich gate'ów

$$+ \mathbf{R}_{ii}\mathbf{i}^{t-1} + \mathbf{R}_{fi}\mathbf{f}^{t-1} + \mathbf{R}_{oi}\mathbf{o}^{t-1}$$



$$\begin{aligned}\mathbf{i}^t &= \mathbf{W}_i \mathbf{x}^t + \mathbf{R}_i \mathbf{y}^{t-1} + \mathbf{p}_i \odot \mathbf{c}^{t-1} + \mathbf{b}_i \\ &\quad + \mathbf{R}_{ii} \mathbf{i}^{t-1} + \mathbf{R}_{fi} \mathbf{f}^{t-1} + \mathbf{R}_{oi} \mathbf{o}^{t-1} \\ \bar{\mathbf{f}}^t &= \mathbf{W}_f \mathbf{x}^t + \mathbf{R}_f \mathbf{y}^{t-1} + \mathbf{p}_f \odot \mathbf{c}^{t-1} + \mathbf{b}_f \\ &\quad + \mathbf{R}_{if} \mathbf{i}^{t-1} + \mathbf{R}_{ff} \mathbf{f}^{t-1} + \mathbf{R}_{of} \mathbf{o}^{t-1} \\ \bar{\mathbf{o}}^t &= \mathbf{W}_o \mathbf{x}^t + \mathbf{R}_o \mathbf{y}^{t-1} + \mathbf{p}_o \odot \mathbf{c}^{t-1} + \mathbf{b}_o \\ &\quad + \mathbf{R}_{io} \mathbf{i}^{t-1} + \mathbf{R}_{fo} \mathbf{f}^{t-1} + \mathbf{R}_{oo} \mathbf{o}^{t-1}\end{aligned}$$

Trzy benchmarki



Benchmarki / architektury

- TIMIT - rozpoznawanie mowy (fonetyczne)
 - 1 warstwa, dwukierunkowy LSTM
- IAM Online - rozpoznawanie pisma
 - 1 warstwa, dwukierunkowy LSTM
- JSB Chorales - predykcja muzyki
 - 1 warstwa, jednokierunkowy LSTM

Ben Zuma said: "The days of thy life noons in the day-time; all the days of thy life noons even at night-time." (Berachah.) And the Rabbis thought it important that when we read the

Eksperymenty i wyniki

Eksperymenty

- każdy wariant x każdy benchmark
- random search hiperparametrów:
 - rozmiar warstwy
 - szum na wejściu
 - momentum
 - learning rate



Kula Zorba tocząca się w dół zbocza, obrazująca dążenie do minimum funkcji straty, iStock.

Wyniki

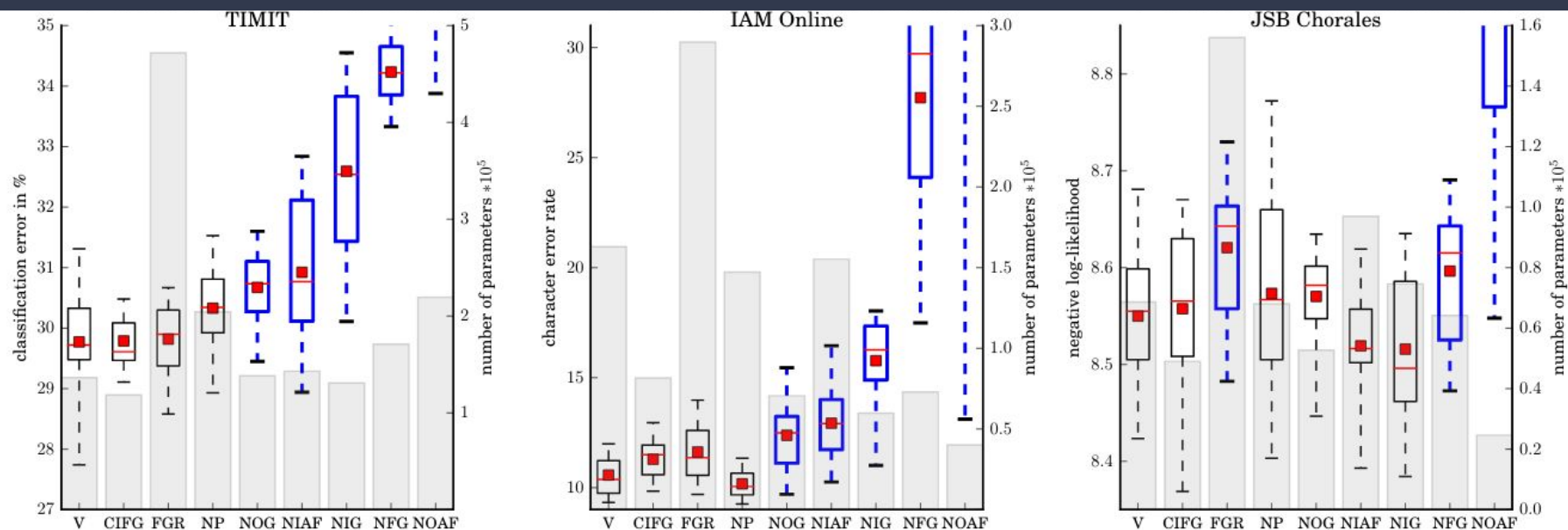
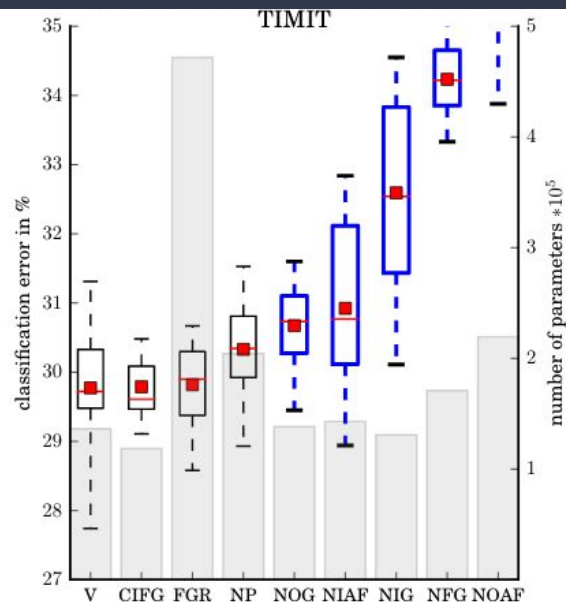


Figure 3. *Test set* performance for all 200 trials (top) and for the best 10% (bottom) trials (according to the *validation set*) for each dataset and variant. Boxes show the range between the 25th and the 75th percentile of the data, while the whiskers indicate the whole range. The red dot represents the mean and the red line the median of the data. The boxes of variants that differ significantly from the vanilla LSTM are shown in blue with thick lines. The grey histogram in the background presents the average number of parameters for the top 10% performers of every variant.

Wyniki

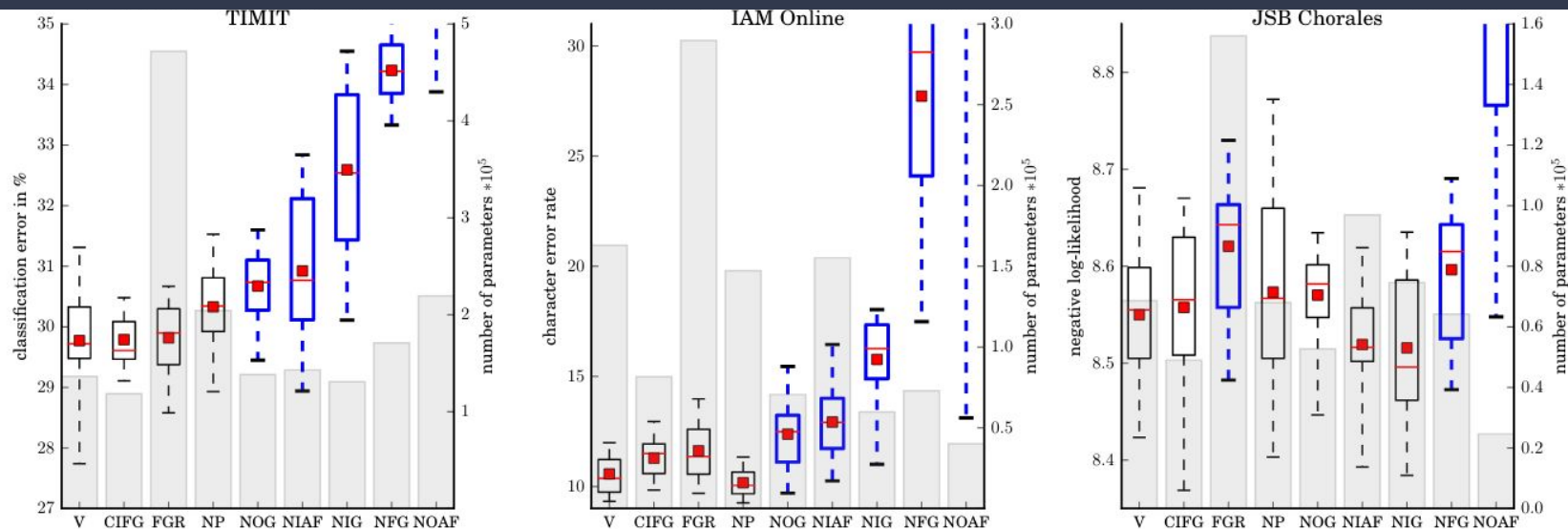


V - Vanilla,
CFIG - Coupled Input Forget Gates,
FGR - Full Gate Recurrence,
NP - No Peepholes,
NOG - No Output Gate,
NIAF - No Input Activation Function,
NIG - No Input Gate,
NFG - No Forget Gate,
NOAF - No Output Activation Function

- Output Activation, Forget Gate - bardzo ważne!
- ...ale już CFIG nadal radzi sobie dobrze
- NP - nieznaczne zmiany w wynikach...
- FGR nie pomaga, ale dodaje parametrów
- NIG, NOG, NIAF - gorzej w rozpoznawaniu pisma i mowy, ale dla muzyki ok.

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