Optical Character Recognition (OCR)

- CV

  Tesseract 3 (A*)
  Binarizuje, naporcuje obrazok na kúsky a snaží sa z nich poskladat symboly

- CNN+RNN

  Pre každý pixel povie pravdepodobnosť že je súčasťou textu, z oblastí z vysokou pravdepodobnosťou spraví obdĺžniky a tieto rozpoznáva rekurentnou neurónovou sieťou

- Holistic

  Zákoduje obraz na príznakovú mapu a z nej generuje texty (transformer typu encoder-decoder)

Vstup

technical details are too complex to cover in the book itself.

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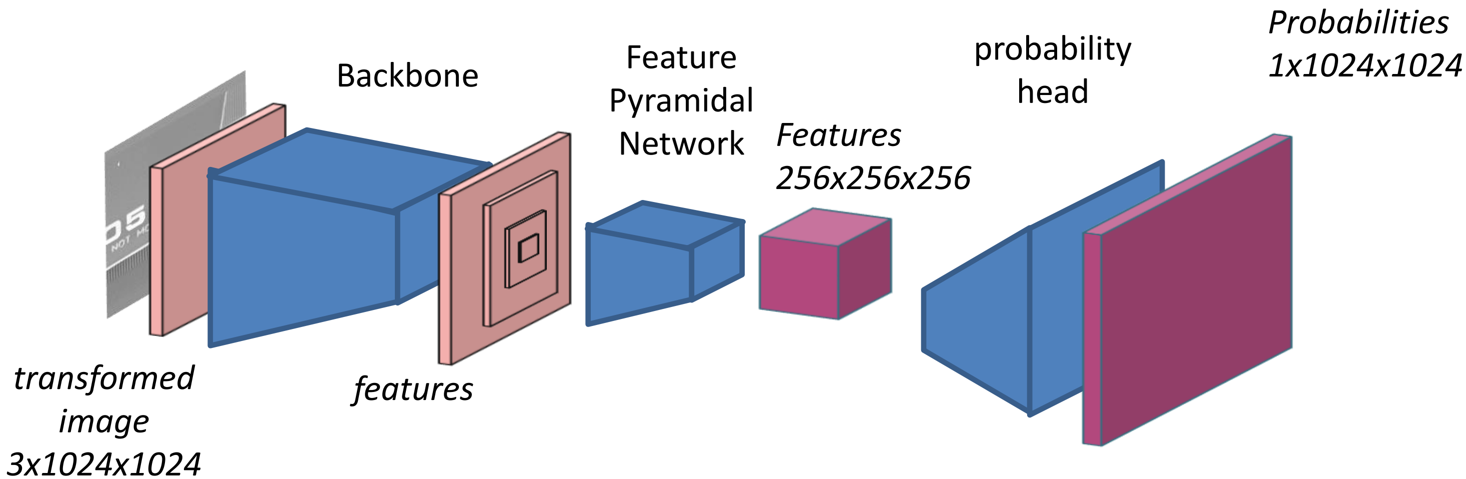
CNN+RNN

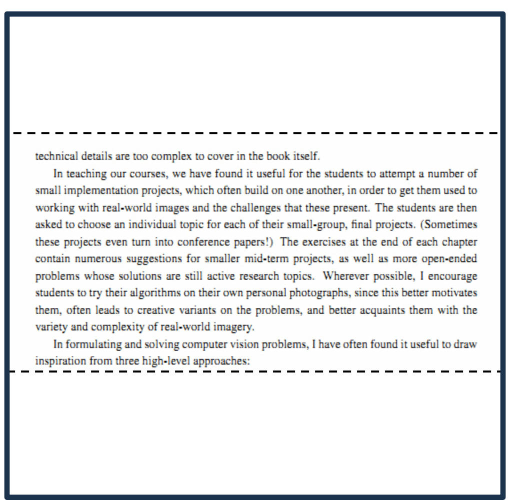
OCR tohto druhu sa skladá z dvoch hlbokých modelov:

- Detektor textu (konvolučná sieť)
- Rozpoznávač textu (dvojsmerná rekurentná sieť)

Výstup prvého je so vstupom druhého prepojený algoritmami klasického počítačového videnia

Detektor textu

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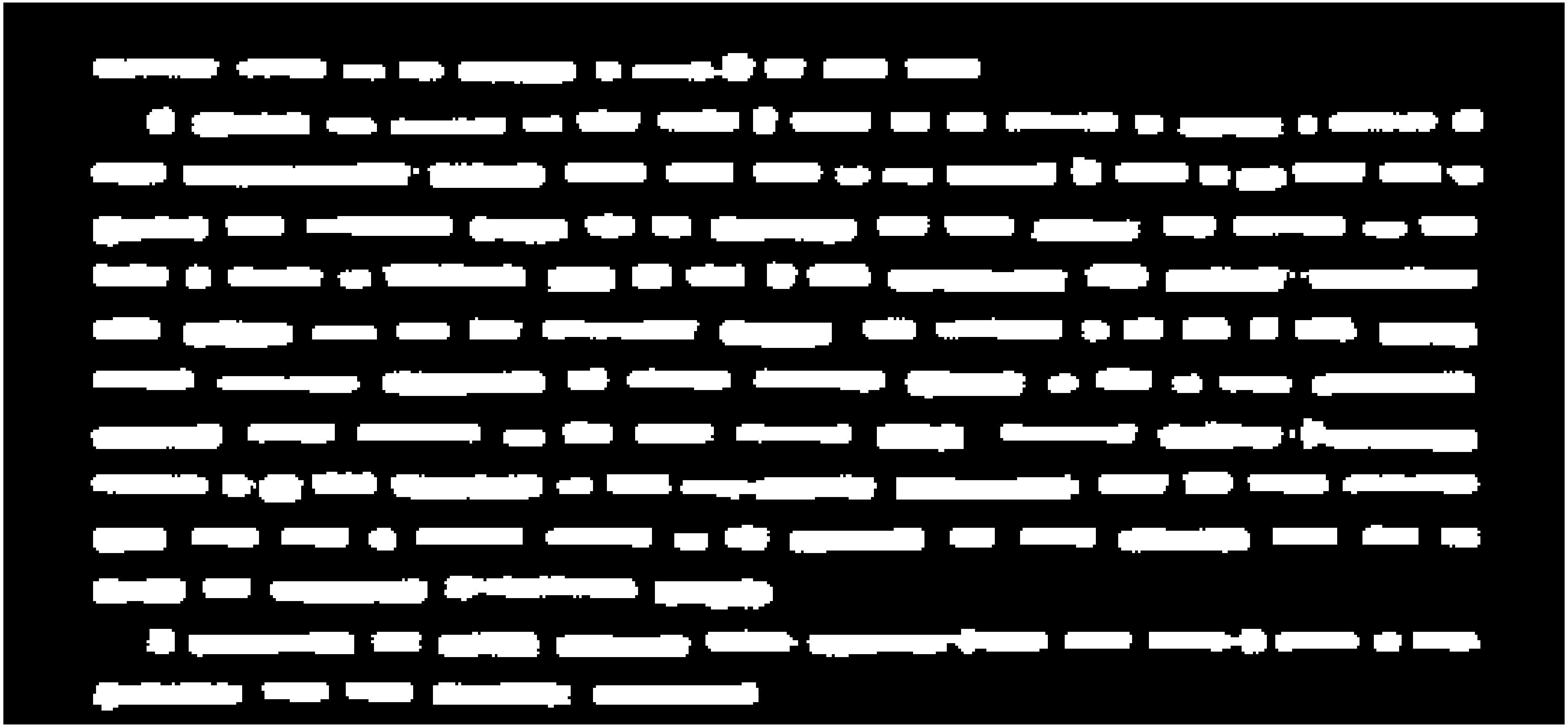
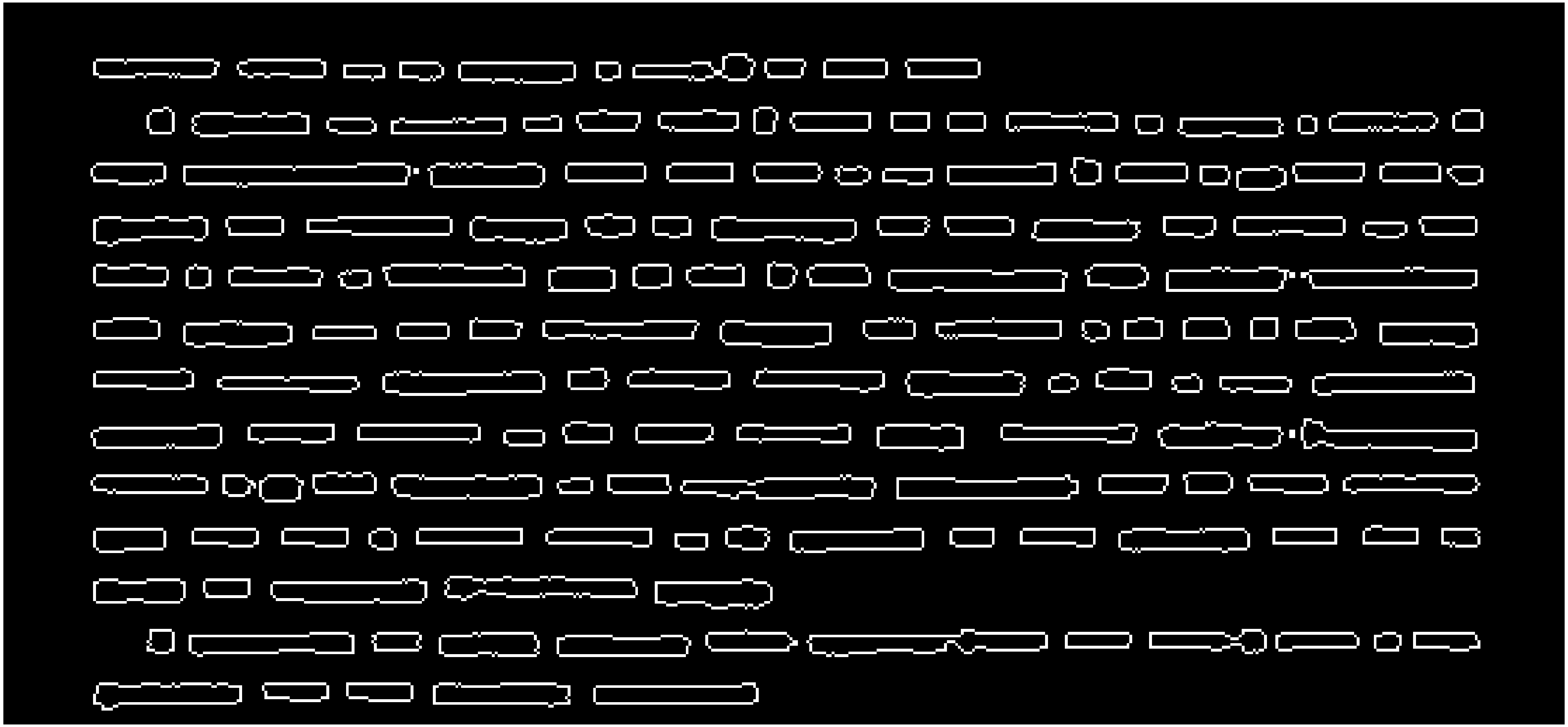
Výstup detektora

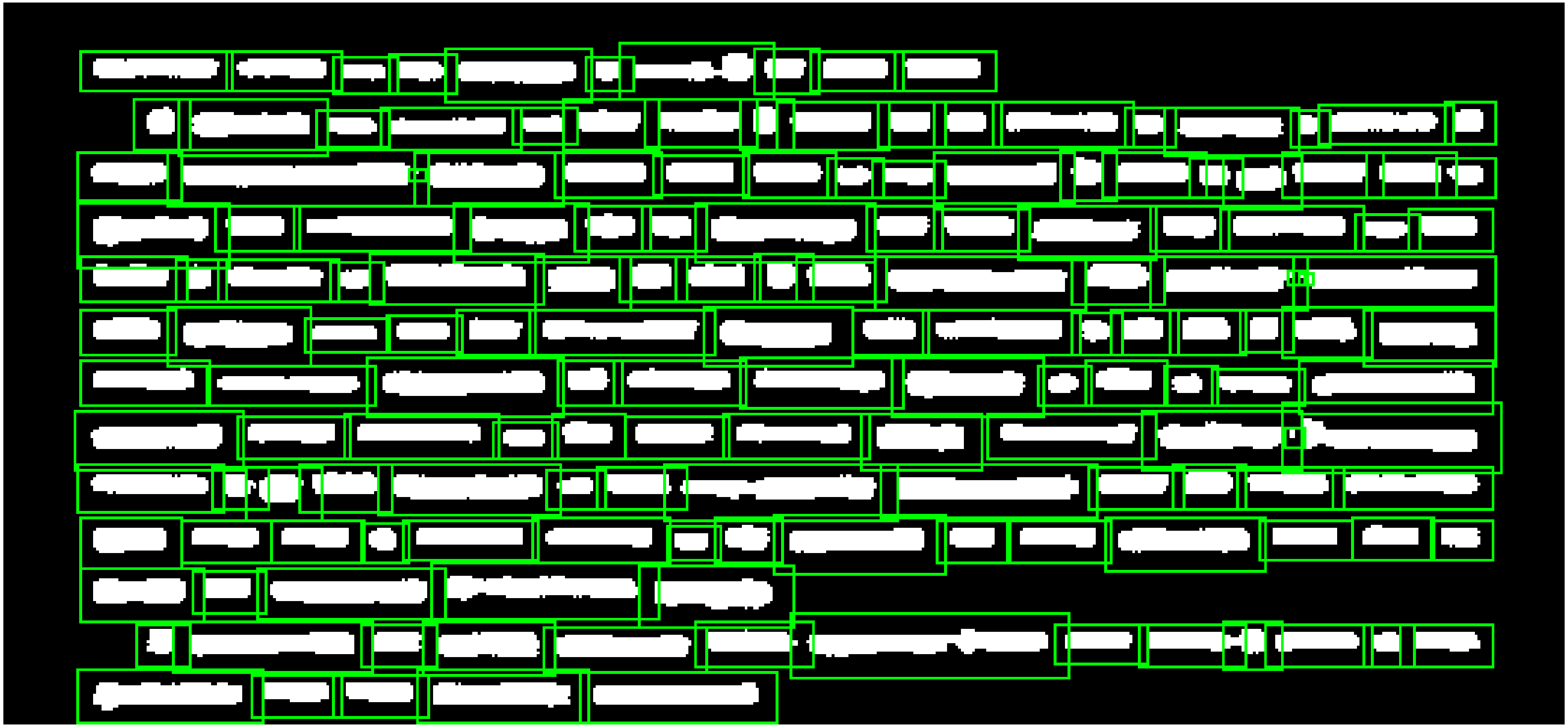


Kontúry



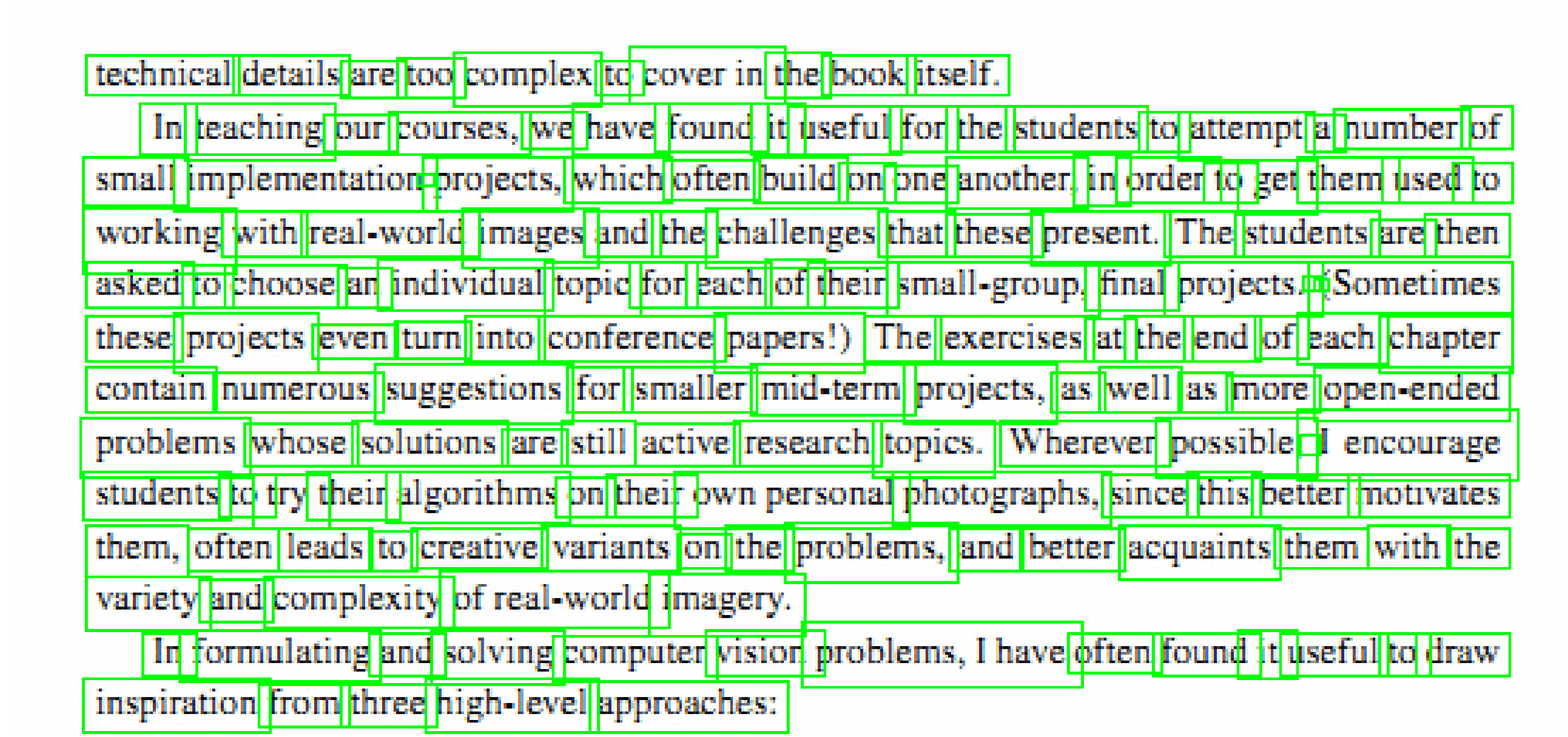
Kontúry môžeme aproximovať štyrmi alebo viacerými bodmi

Obdĺžniky alebo Polygóny



Pritom oblasti zodpovedajúco zväčšíme, aby sme zachytili celý text

Výsledok spracovania detekcie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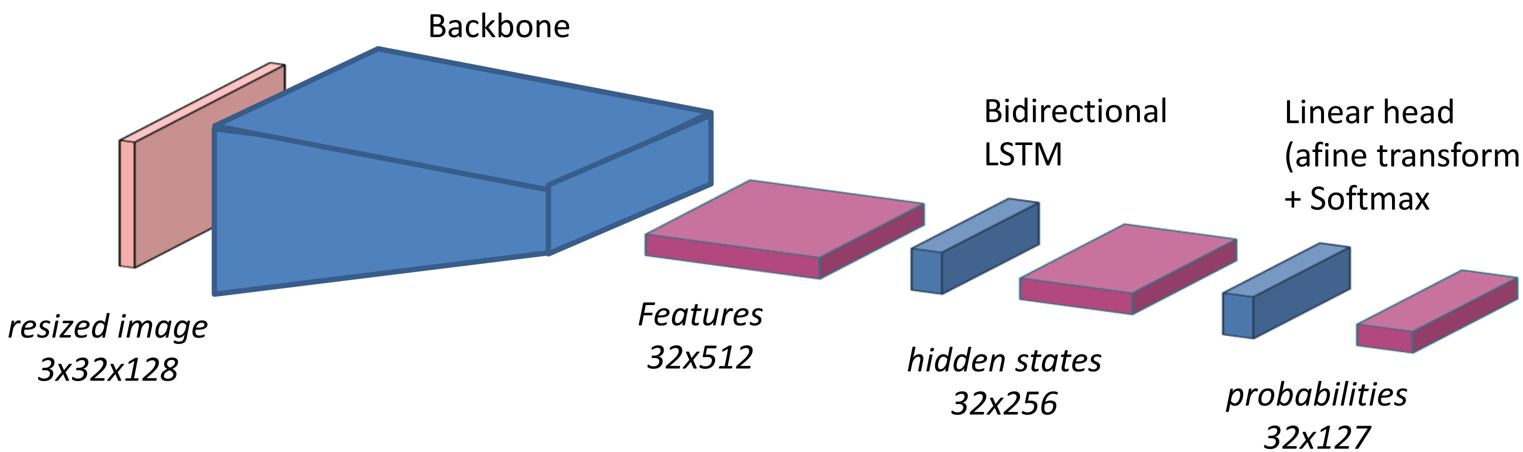
Každý obĺžnik či polygón vyjmene z textu a budeme rozpoznávať

Rozpoznávač



vocab (126 characters):

0123456789abcdefghijklmnopqrstuvwxyzABCD
EFGHIJKLMNOPQRSTUVWXYZ!"#$%&'()*+,-
./:;<=>?@[\]^_`{|}~°£€¥¢฿
àâéèêëîïôùûüçÀÂÉÈÊËÎÏÔÙÛÜÇ

Rozpoznávanie

- Vyrežeme kúsok textu

- Upravíme jeho veľkosť na 32x128

- Tento obraz premeníme na mapu príznakov 32x512
- Tú dekódujeme cez LSTM (typ RNN) na skryté stavy 32x256
- Lineárnou hlavou ich premeníme na 32xN logitov, kde N je počet znakov + 1 (BLANK), aplikujeme softmax
- Cez CTC z pravdepodobností vyberieme symboly

Problém s rýchlosťou

- Dvojsmerná (bidirectional) RNN je schopná pracovať na texte rôznej dĺžky (je naťahovacia)
- Ale nevie pracovať na textoch rôznej dĺžky naraz v jednej dávke
- Preto DocTR radšej naseká texty tak, aby mali menej ako 32 symbolov a používame rovnako veľký vstup 3x32x128
- (Ale Pytorch vie pustiť rôzne dĺžky naraz, akurát vyžaduje aby bola dávka utriedená podľa dĺžky zostupne takže treba urobiť správnu permutáciu)

Výstup

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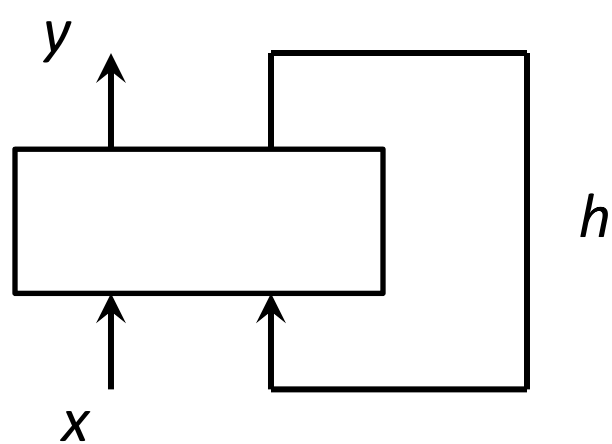
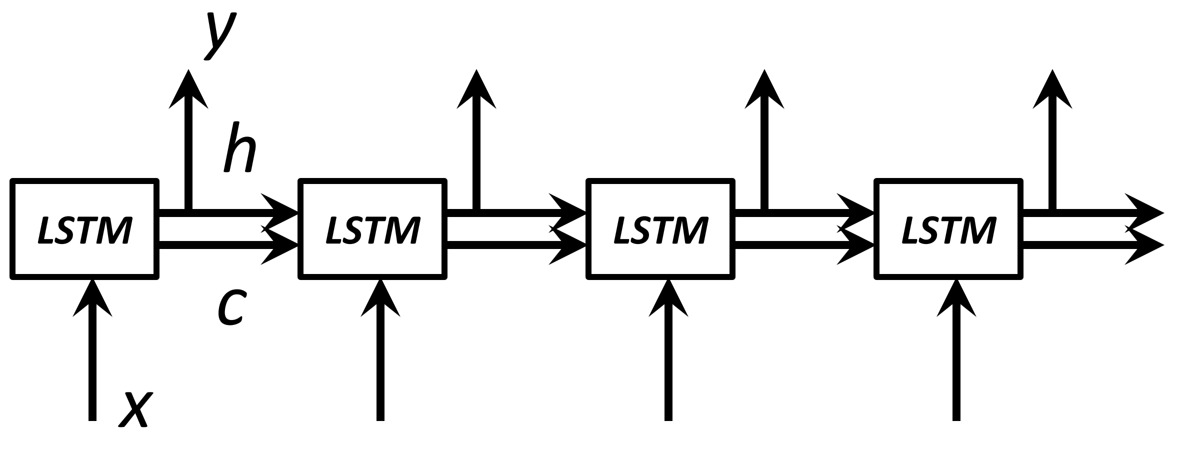
Rekurentná neurónová sieť

- Sieť inšpirovaná spracúvaním postupnosti dát v čase
- V každom okamihu dostáva nový vstup, dáva nový výstup a skrytý stav sa zapamätá a bude pridaný na vstup v ďalšom okamihu



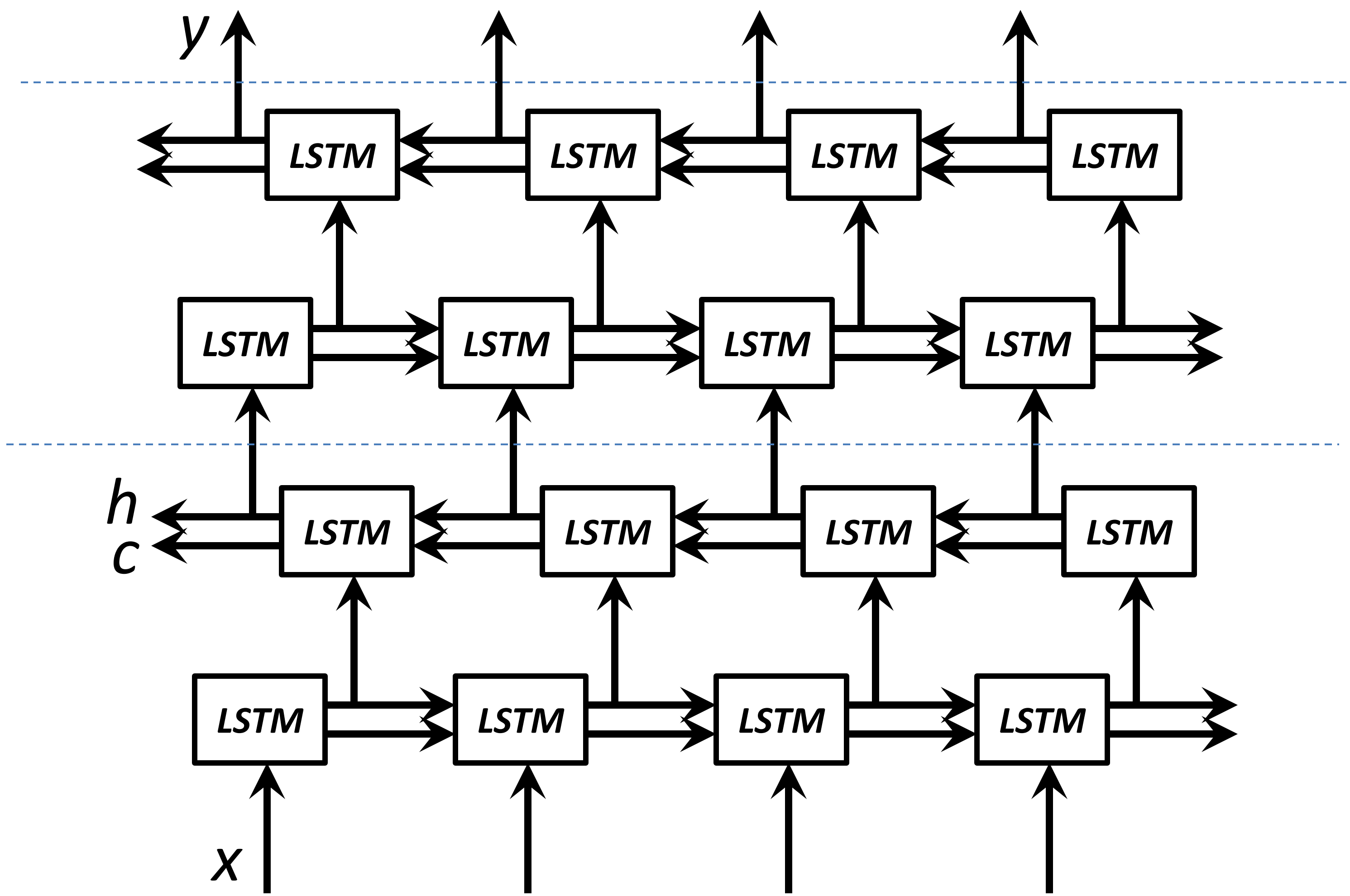
RNN

- Reálne sa nepúšťa na dáta postupne v čase, ale na konci naraz



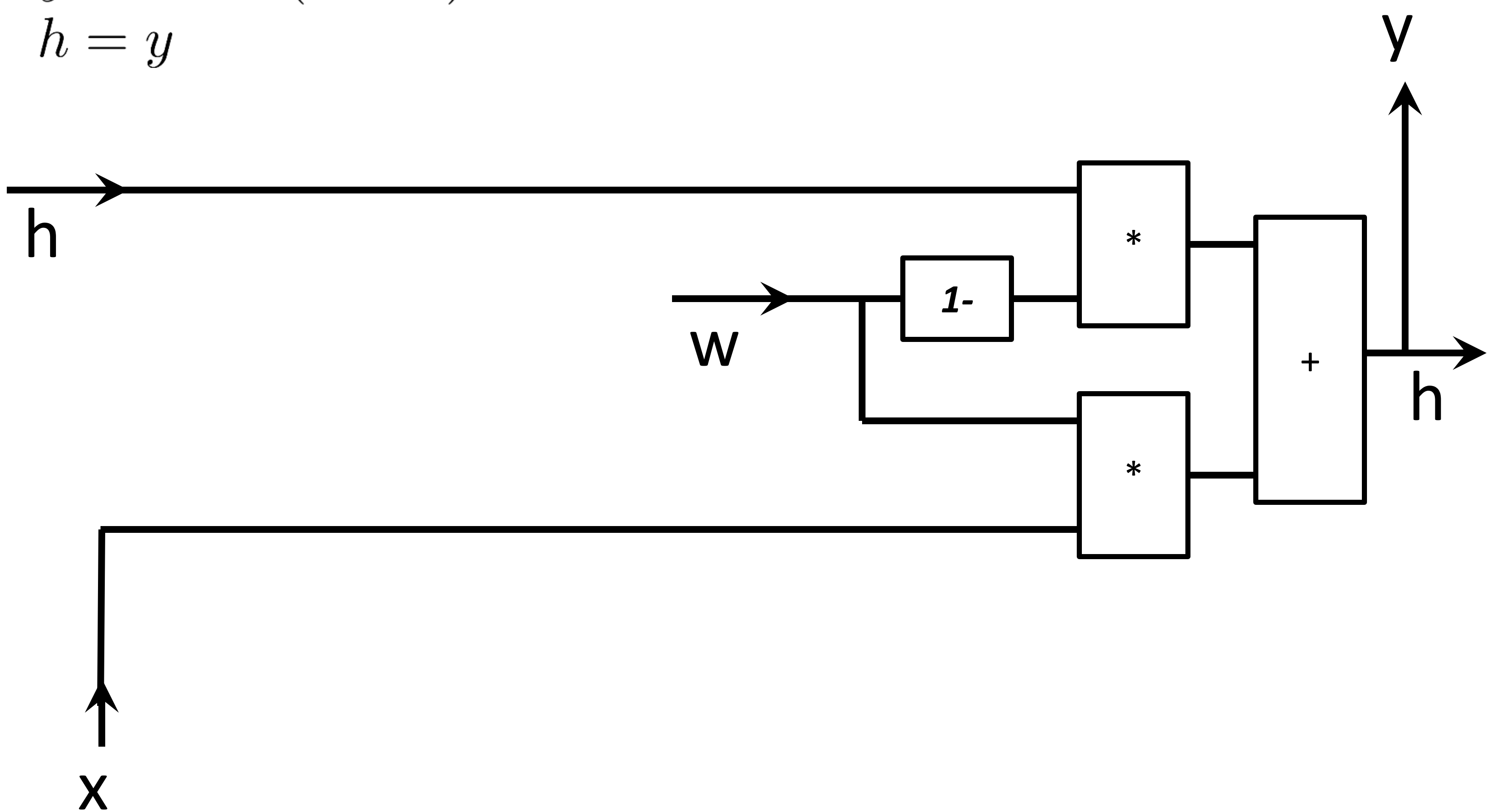
- počet LSTM modulov je daný dĺžkou vstupu

Bidirectional RNN

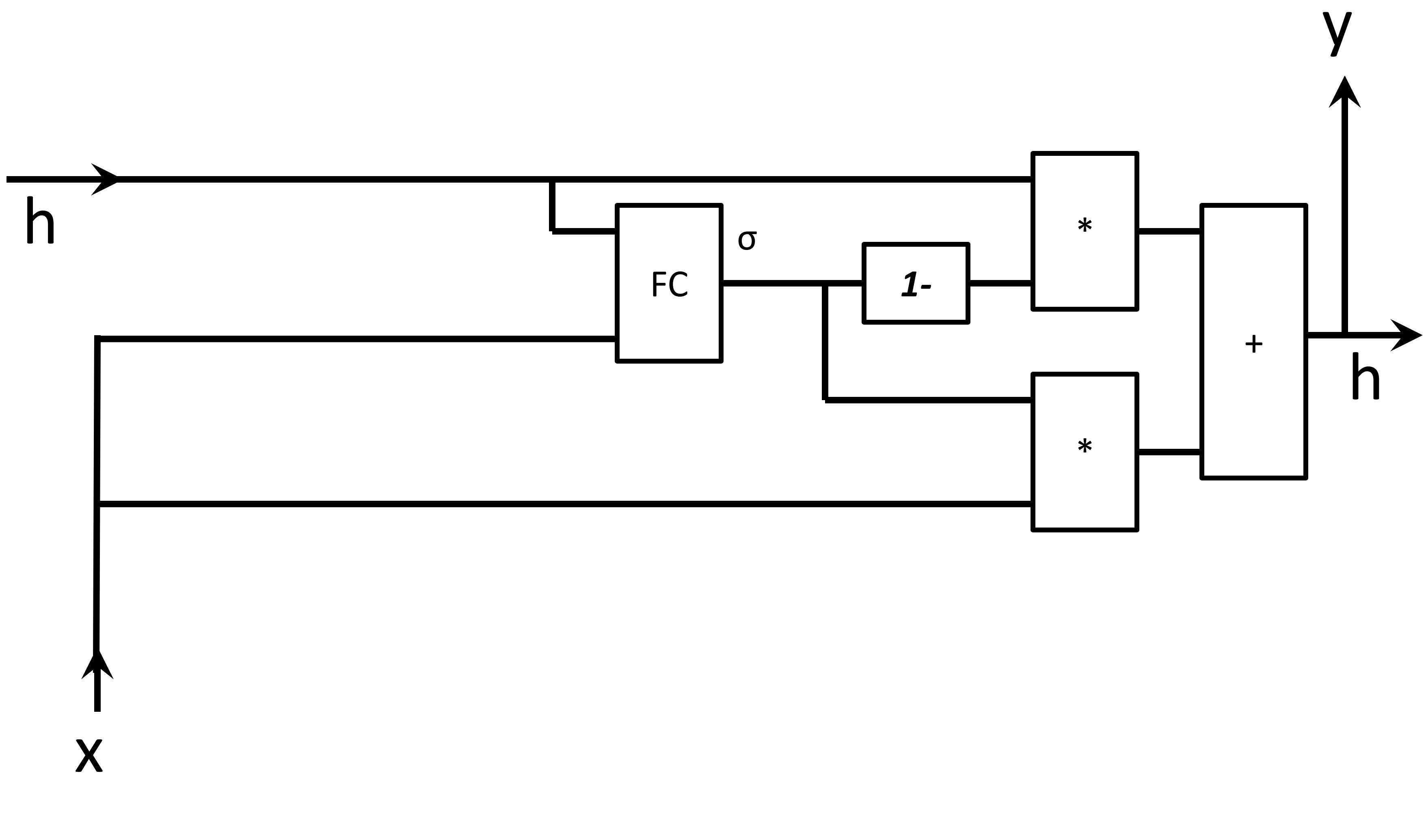


```
x: -1,-1,-1,-1,-1,-1,1,1,1,1,-1,1,1,1,1,1,1,-1,1,1,1,1,1…
y: 0,-0.4,-0.7,-0.9,-1,-0.9,-0.7,-0.4,0.1,0.5,0.9,1,1,1,1,…
```

$$y = wx + (1-w)h$$
$$h = y$$



dimension of x, y and h can be > 1



y
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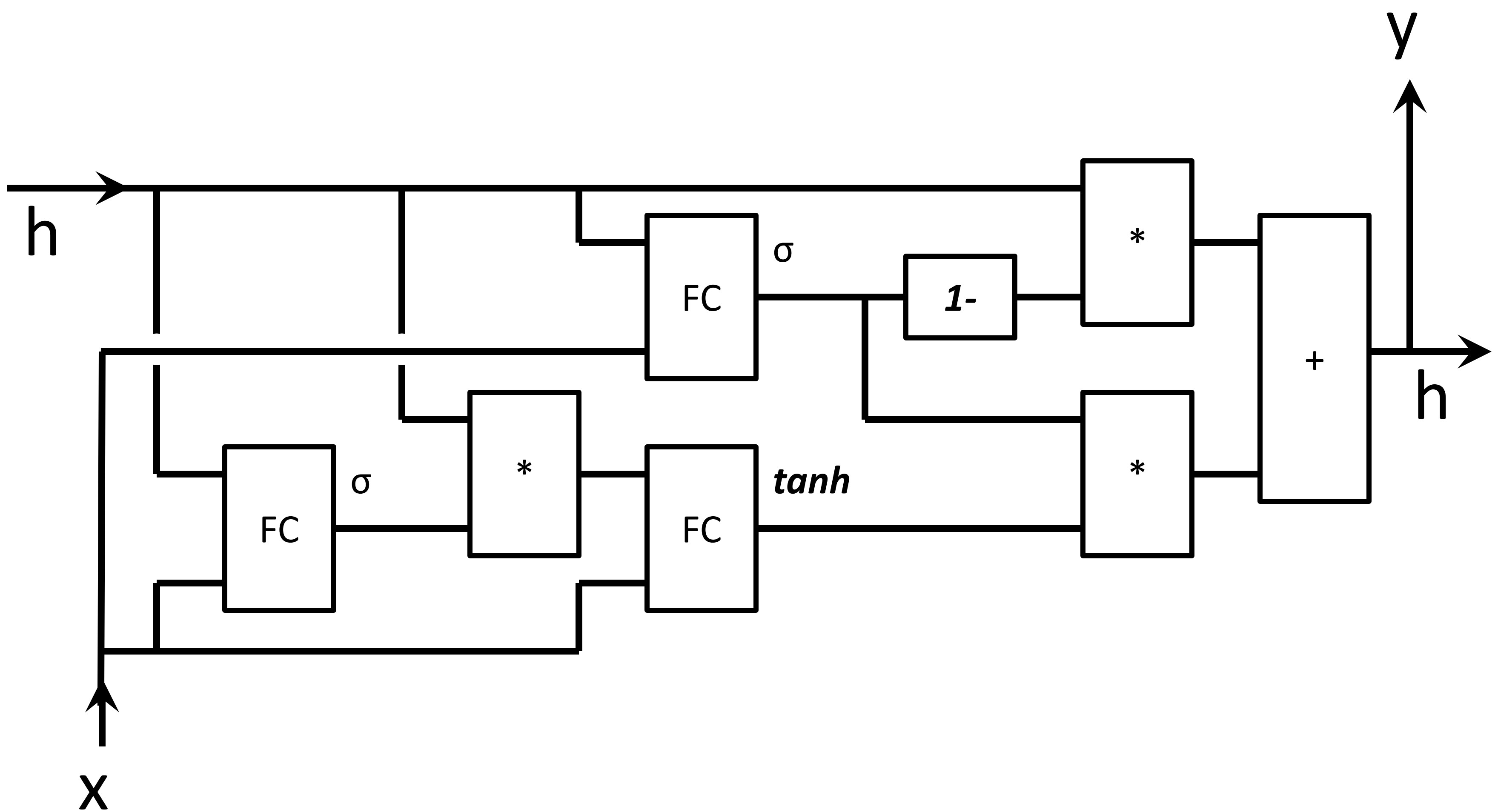
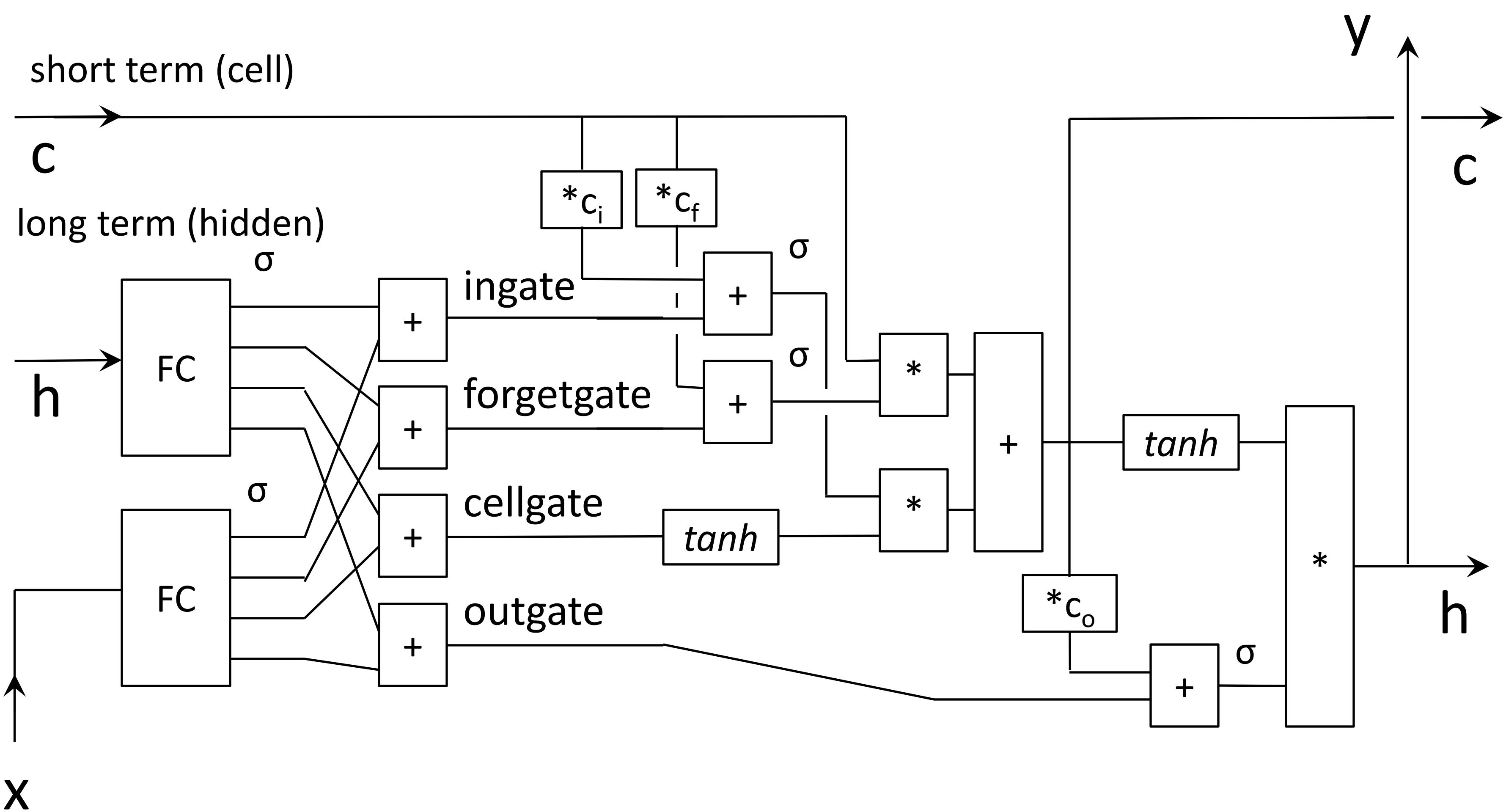
x

Gated recurrent unit (GRU)



Long Short-Term Memory (LSTM)



Connectionist Temporal Classification (CTC)

- Chybová funkcia
- Počíta sumu pravdepodobností pre všetky možné zarovnania
- Zarovnanie je cesta cez tenzor pravdepodobností, ktorá pod odstránení BLANKu dáva požadovanú sekvenciu; pravdepodobnosť cesty je súčinom pravdepodobností krokov
- Počíta sa efektívne cez dynamické programovanie

Connectionist Temporal Classification (CTC)

- Ako vedľajší produkt vie vypočítať najpravdepodobnejšiu cestu, takže ju je možné použiť aj na dekódovanie pri inferencii (beam search)
- Po natrénovaní však celkom dobre funguje aj greedy: pre každý výstup sa vezme najpravdepodobnejší symbol
- Rozdiel: beam nájde cestu s najväčším súčinom pravdepodobností, greedy s najväčším súčtom