Detecting Asymmetric Semantic Relations in Context

A Case Study on Hypernymy Detection

Yogarshi Vyas and Marine Carpuat

*SEM 2017 - 08/03/2017

Chess $\xrightarrow{\textbf{Hypernym?}}$ Game

Chess → Game ✓

Magnus Carlsen is the world **chess** champion

Hypernym?

The championship **game** was played in NYC.

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Hypernym?

The poachers hunted the big **game**

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Hypernymy Detection in Context

Input

Output

Hypernymy Detection in Context

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chess **game**

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✓ if game is a hypernym of chess in the given contexts

✗

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Motivation : Why Context?

- Benefit downstream tasks
  - Question Answering
  - Textual Inference

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- Benefit downstream tasks
  - Question Answering
  - Textual Inference
- Previous work relies on annotator to think about senses
  (Hearst, 1992; Zhitomirsky-Geffet and Dagan, 2009; Turney and Mohammad, 2013)

Previous Work

Previous Work : Context-PPDB

Shwartz and Dagan, *SEM 2016

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- A dataset for **fine-grained lexical inference** in context
- 3750 examples, distributed over **6 semantic relation types**

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Contributions

- We construct **WHiC**, a new dataset of hypernym pairs in context
  - Automatically extracted from **WordNet**!
- WHiC enables
  - **Empirical comparisons** of context embeddings
  - Analysis of **sensitivity to context,** and **directionality**
- We provide experimental evidence of **challenging** nature of task

Outline

- WHiC : A Dataset for Hypernymy Detection in Context
  - Dataset Desiderata
  - Dataset Creation
- Two Models of Context Representation
- Experiments and Analysis

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  - (Chess , Game) **v/s** (Chess , Checkers)
- Large enough to train supervised models

WHiC : WordNet Hypernyms in Context

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Word : Representation
Example : the drawing was not a faithful representation

Word : Drawing, Art
Example : he did complicated pen-and-ink drawings

Word : Study, Sketch
Example : he made several studies before the final painting

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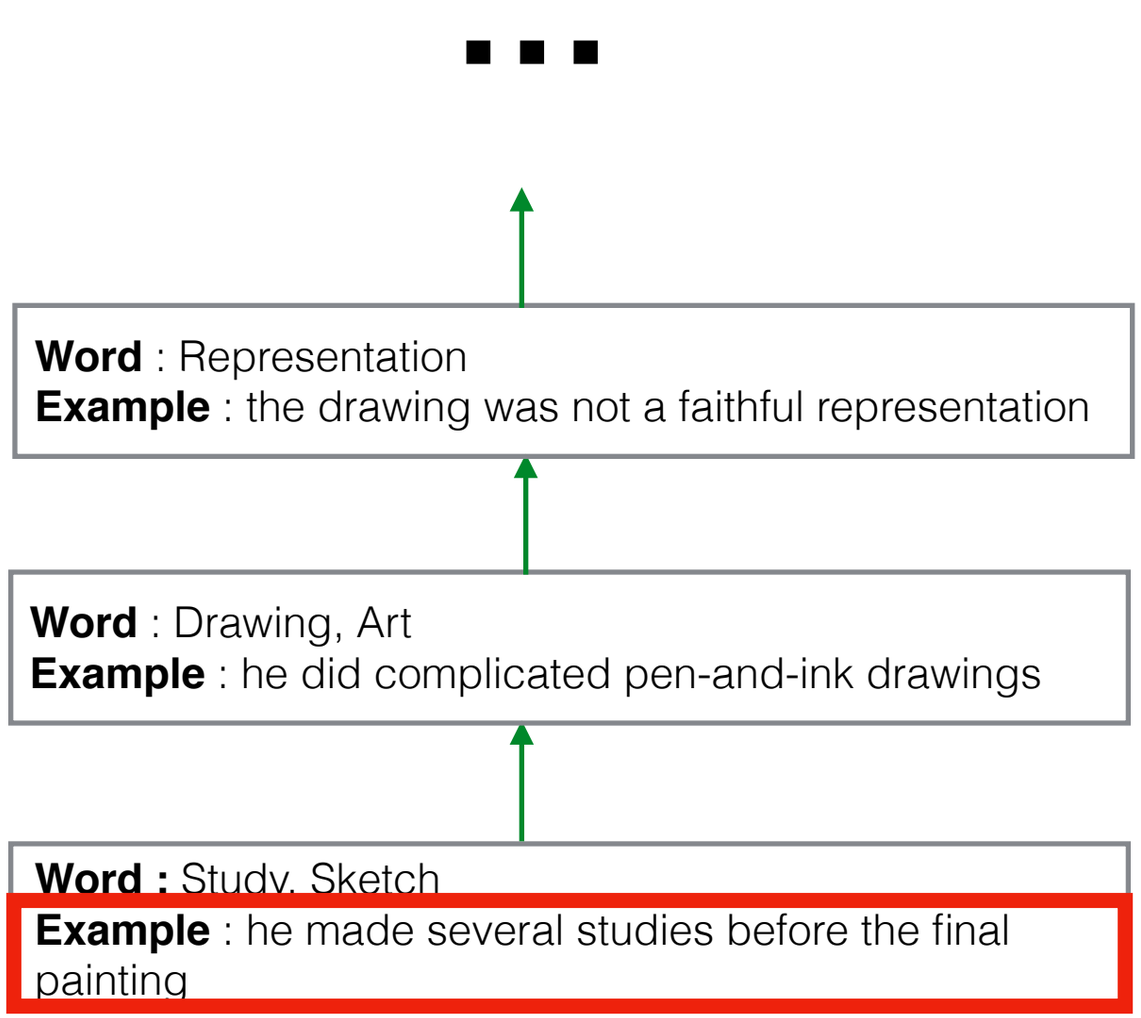

WHiC : Positive Examples

Word : Study
Example : he knocked on the door of the study

Word : Study
Example : he made several studies before the final painting

w_1, w_2	c_1, c_2	IsHypernym(w_1, w_2) ?

WHiC : Positive Examples

Word : Room
Example : the rooms were small but comfortable

Word : Study
Example : he knocked on the door of the study

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w_1, w_2	c_1, c_2	IsHypernym(w_1, w_2) ?
Study, Room	He knocked on the door of the **study** The **rooms** were small but comfortable	✓
Study, Drawing	He made 2 **studies** before the painting He did pen-and-ink **drawings**	✓

WHiC : Negative Examples

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Dataset Desiderata

- Test sensitivity of models to changing contexts ✓
- Differentiate between **hypernymy** and **semantic similarity** ✓
- Large enough to train supervised learning models on ✓
  - Seed vocab = 10k most frequent words from Wikipedia
  - 22000 examples distributed over 6000 word pairs

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Supervised Hypernymy Detection

chess **game**

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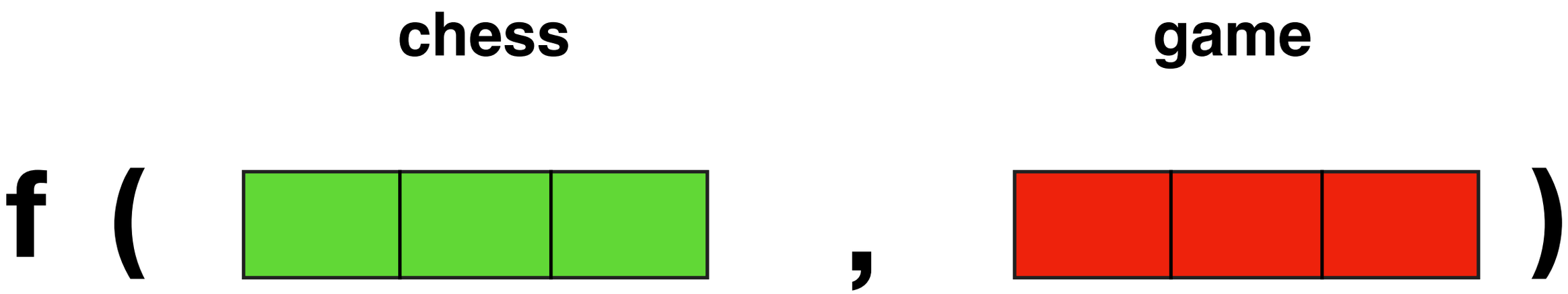

Baroni et al., 2012; Roller et al., 2014; Weeds et al., 2014 *inter alia*

Supervised Hypernymy Detection

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f (,)

x . y **y - x** [**x ; y**]

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Hypernymy-Feature Detector

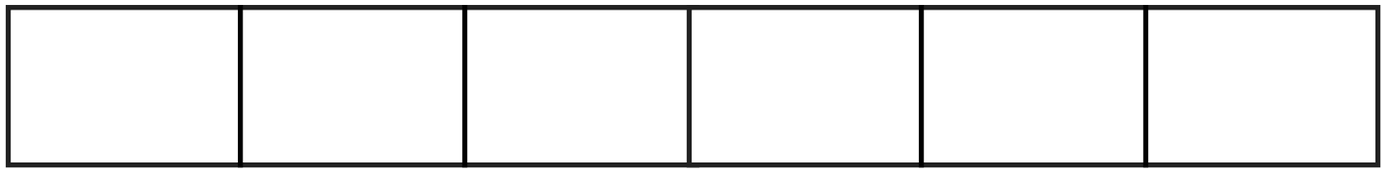
Roller and Erk; EMNLP 2016

Game

Word (w)

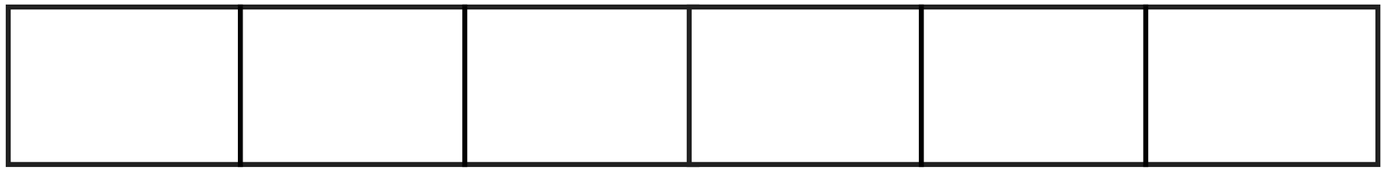
Game

Word (w)



The hunters hunted the **game**

Contextualized Word (w_c)



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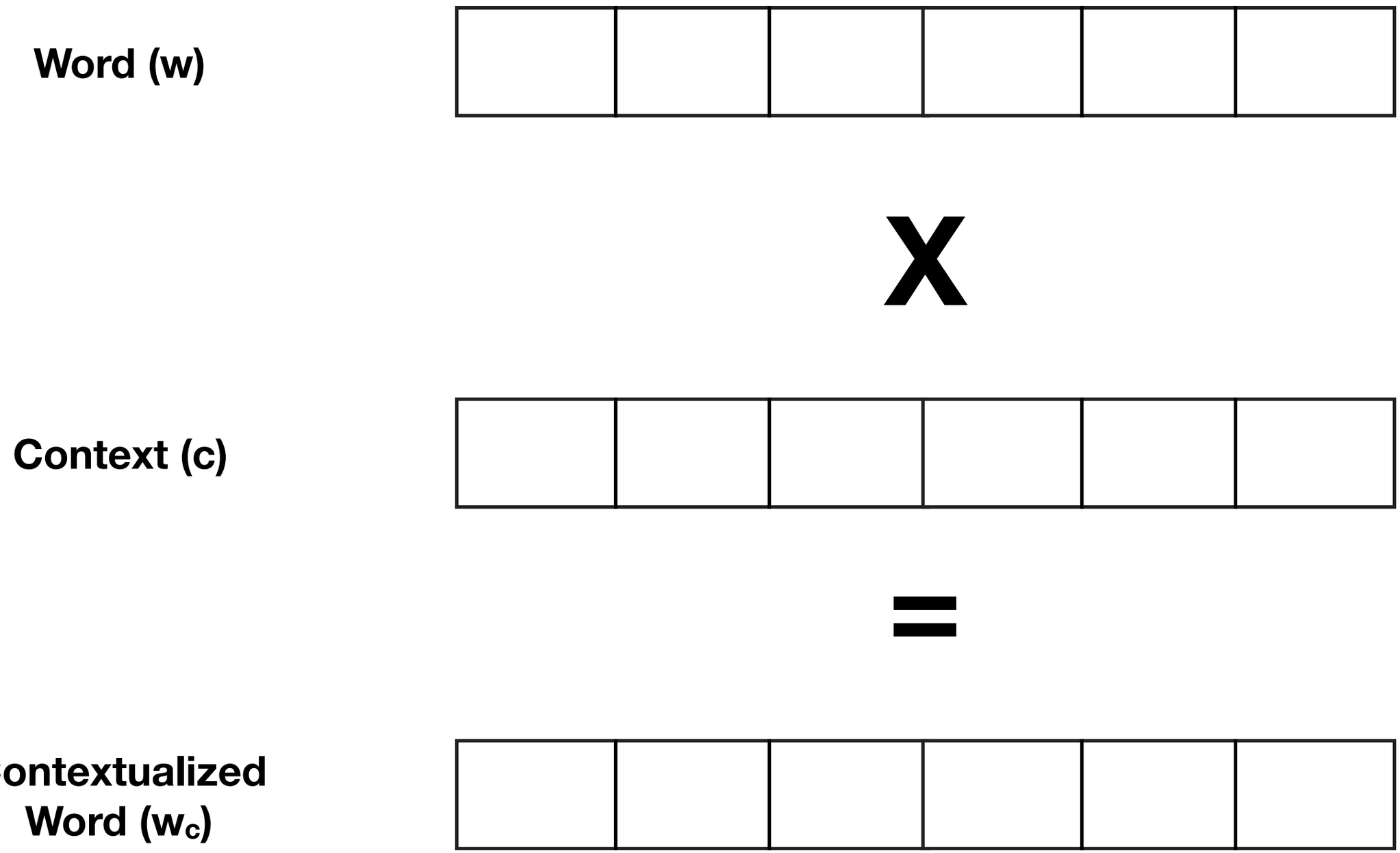

Erk and Padó, EMNLP 2008; Thater et al., IJCNLP 2011; Dinu et al., NAACL 2012

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Representing Context

Two complementary approaches

Representing Context

Two complementary approaches

- **Pooling :** Combining word type representations into context representations
  - Mean, min, and max

Representing Context : Pooling

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the	0.3	0.6	-0.1
river	1.5	-2.5	0
bank	-1	0.2	1.8

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$\vec{c}_{l,mean}$

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$$\vec{c}_l = [\vec{c}_{l,mean} ; \vec{c}_{l,min} ; \vec{c}_{l,max}]$$

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Representing Context

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- **Pooling :** Combining word type representations into context representations
  - Mean, min, and max
- **RNN Composition** : Embed words and contexts jointly

Representing Context : Context2Vec

Melamud et al; CoNLL 2016

Representing Context : Context2Vec

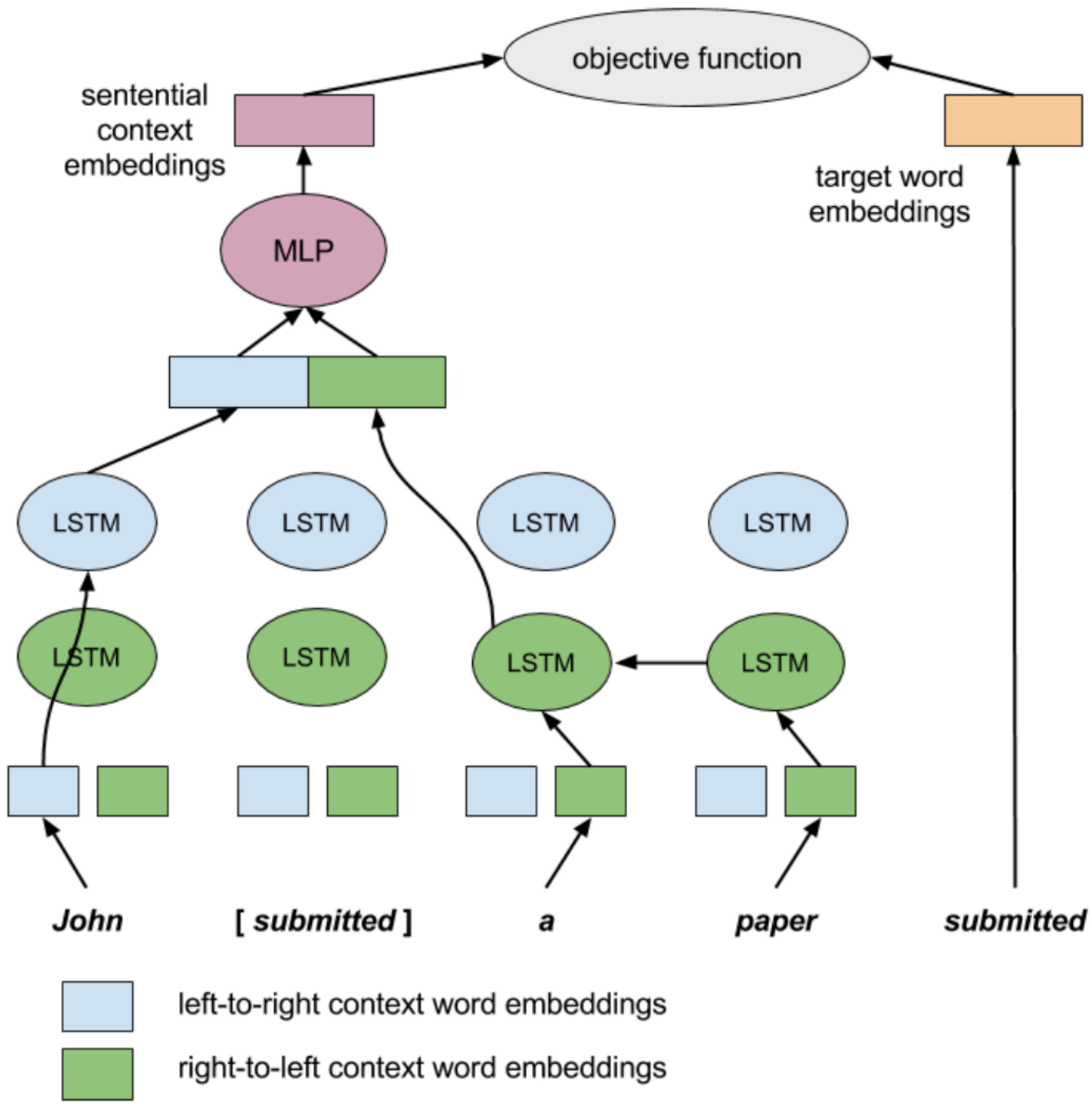
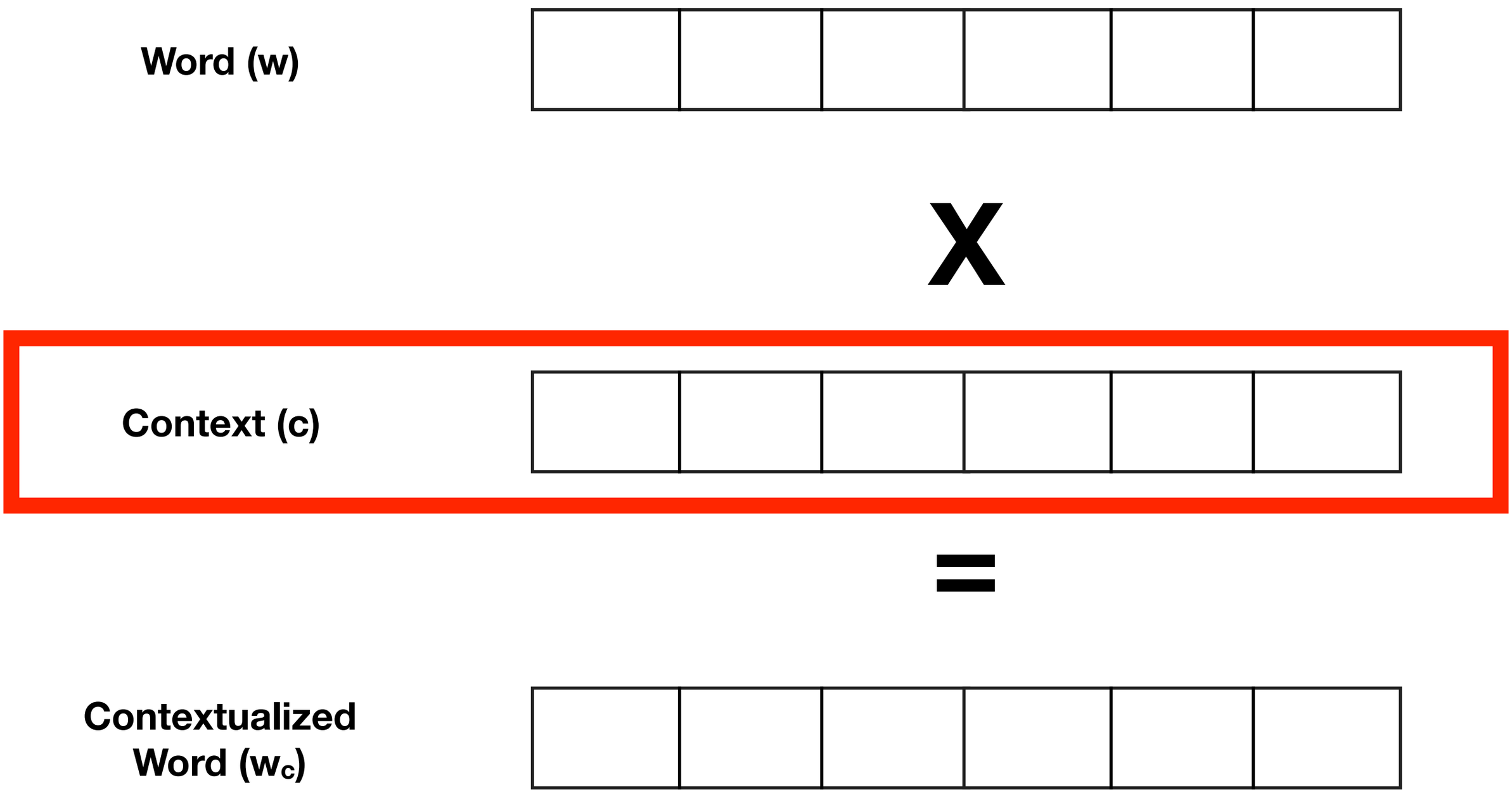


Image courtesy : context2vec: Learning Generic Context Embedding with Bidirectional LSTM, Melamud et al., CoNLL 2016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Context (c)
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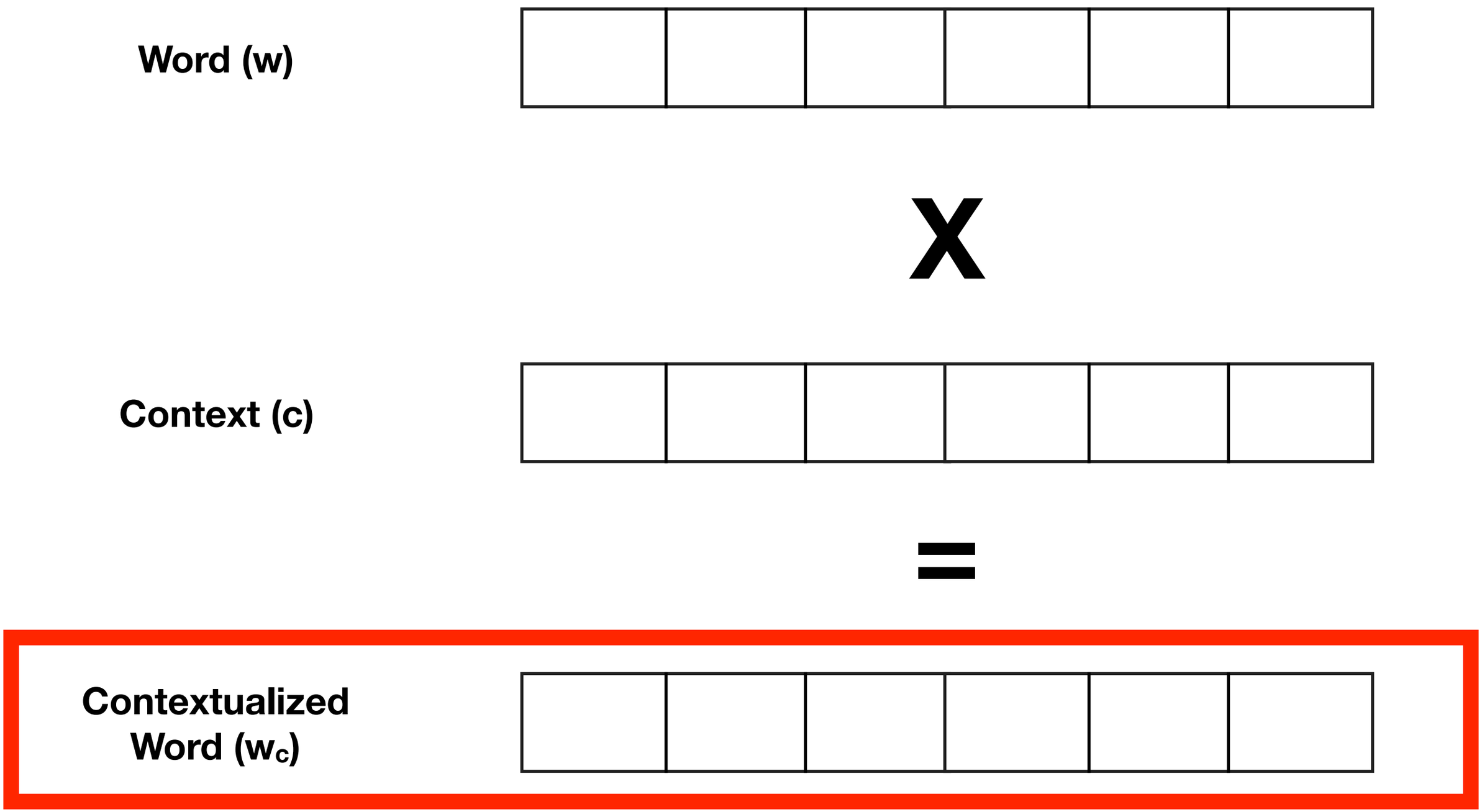
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Putting it all together ..

- **Task** : Context Aware Hypernymy Detection

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- **Dataset** : WHiC
- **Classifier** : H-Feature Detector
- **Input to classifier** : Context aware word representations
  - Pooling
  - Context2Vec

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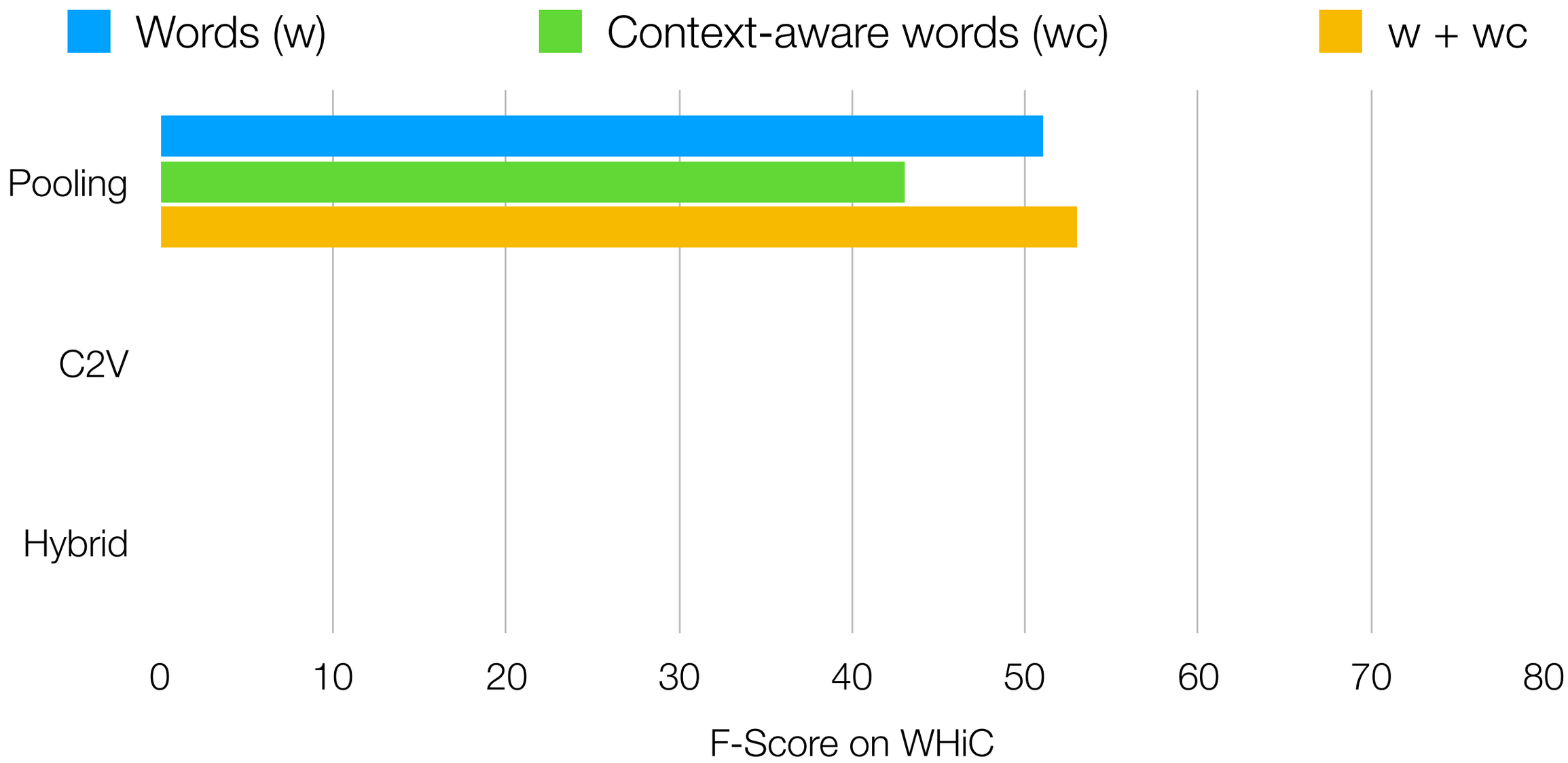
Overall Results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w + wc
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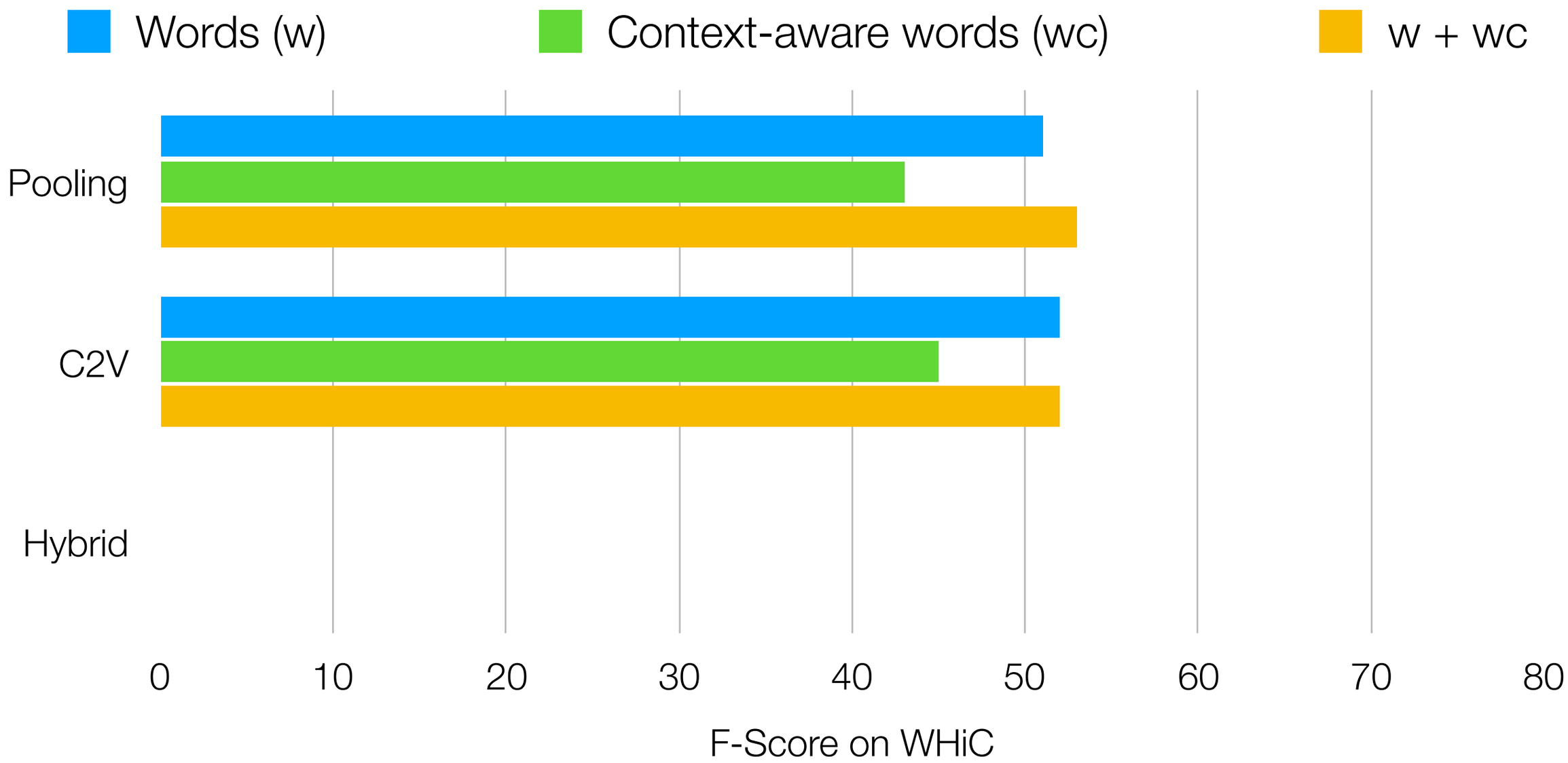
F-Score on WHiC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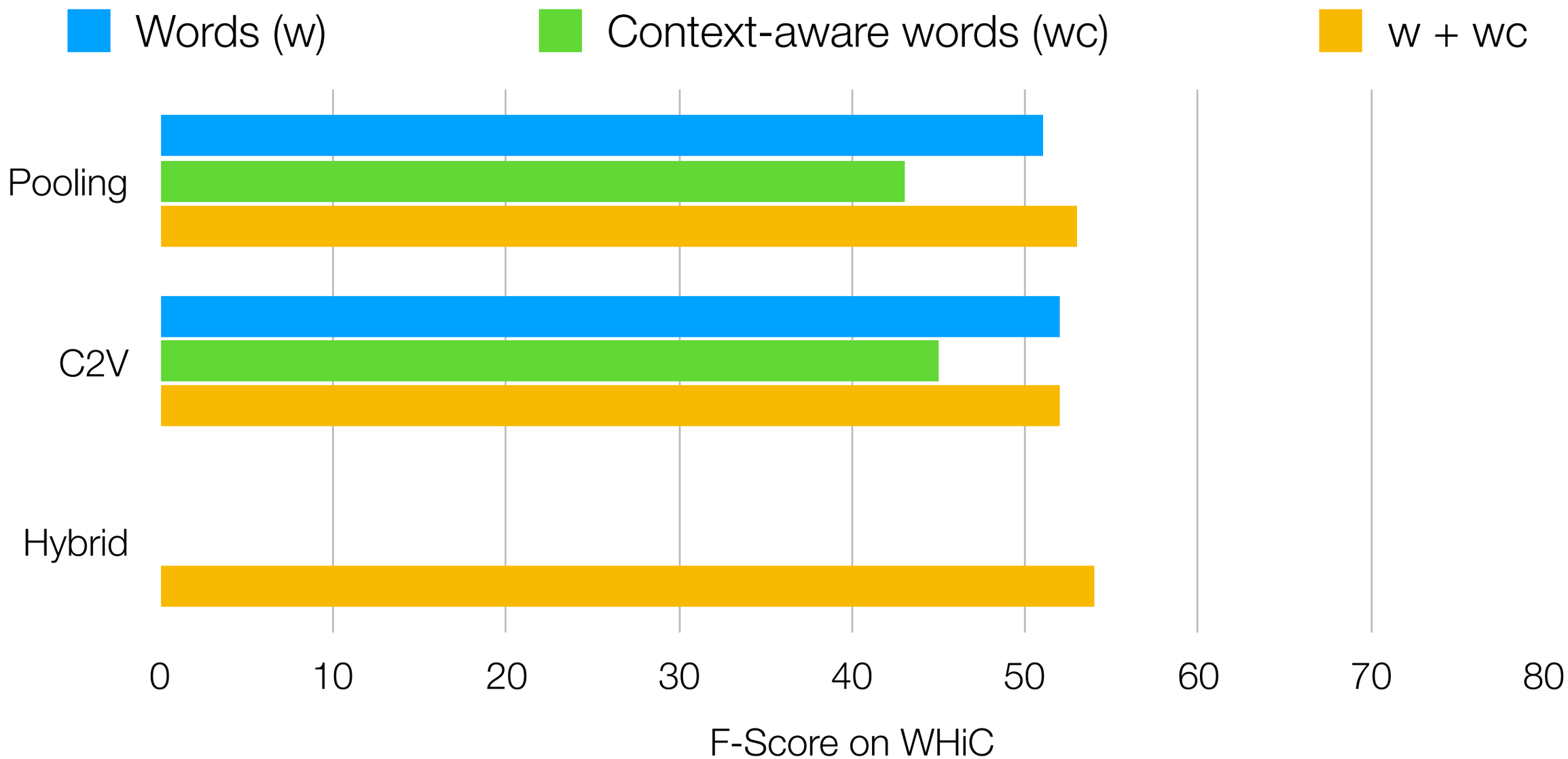
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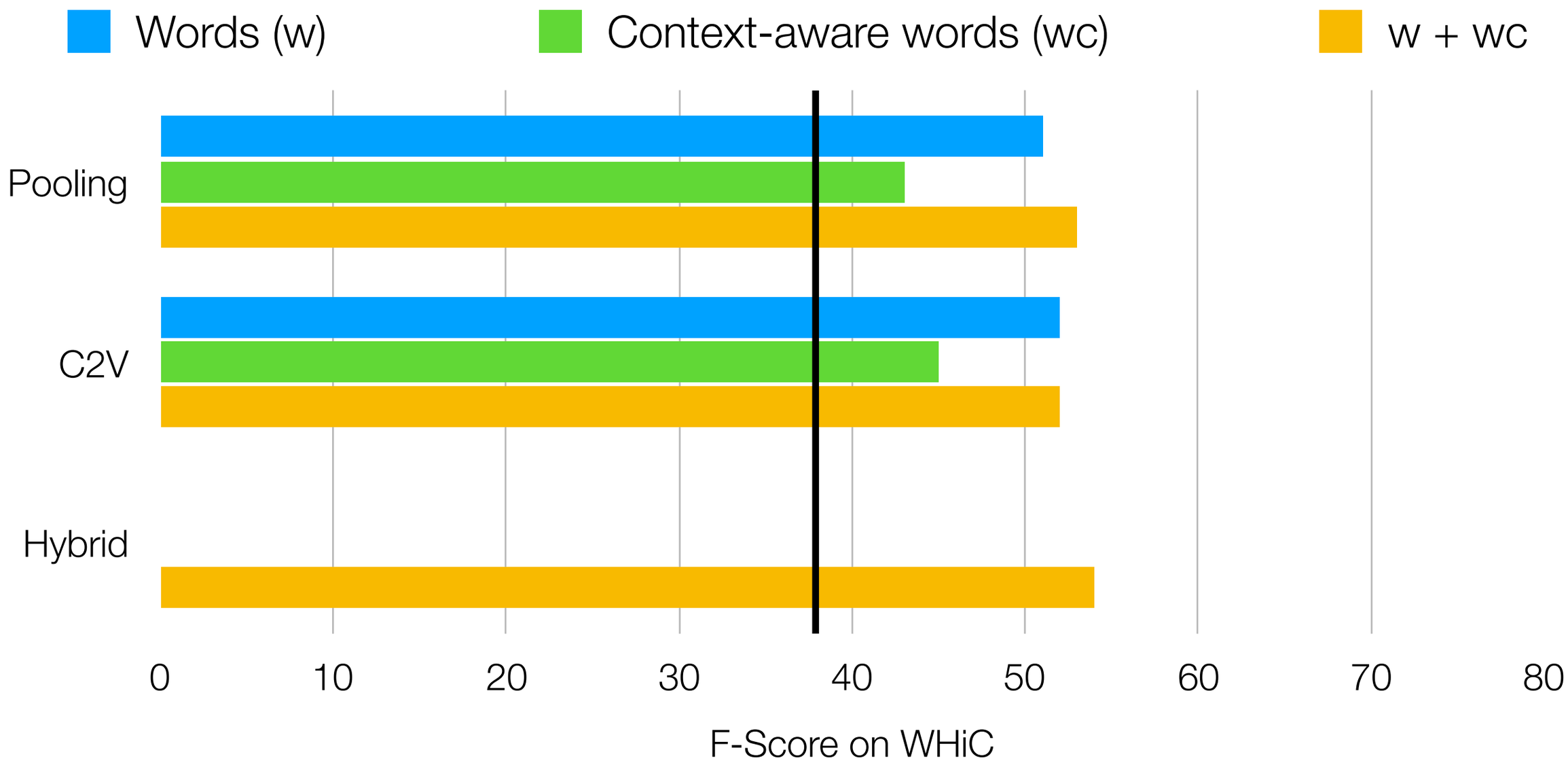
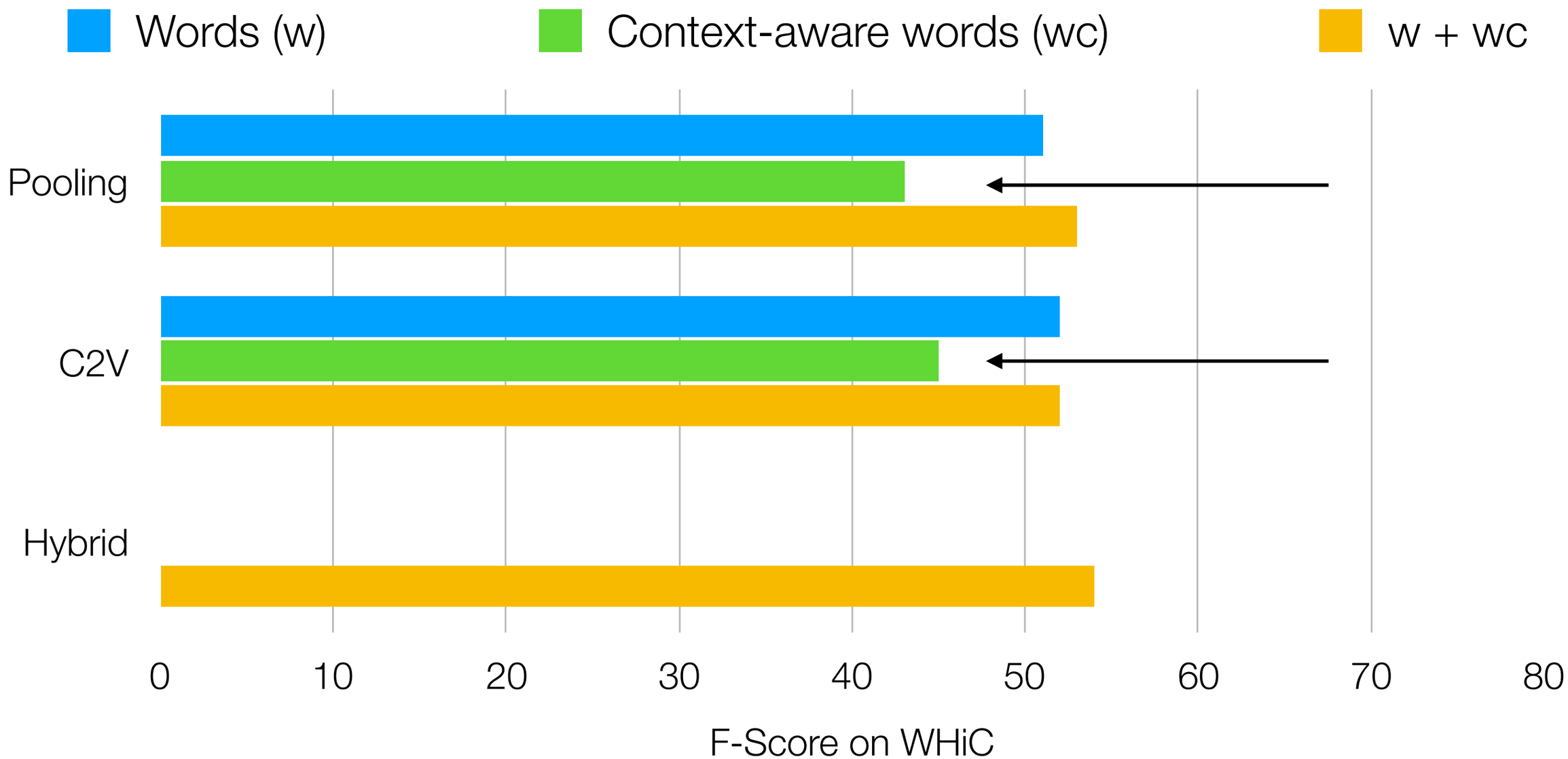


- All models > “All True” Baseline



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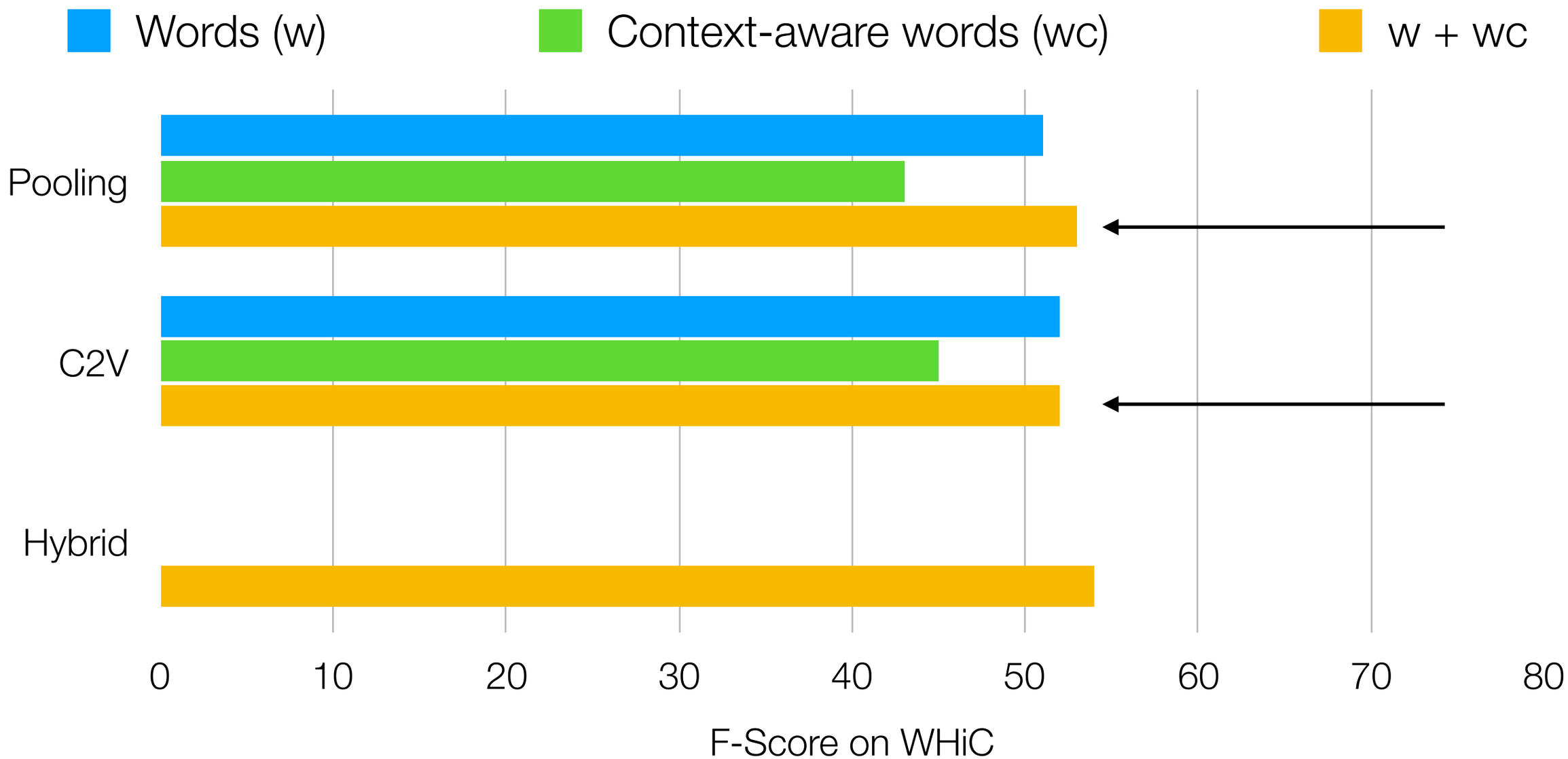
- Context aware representations help ..



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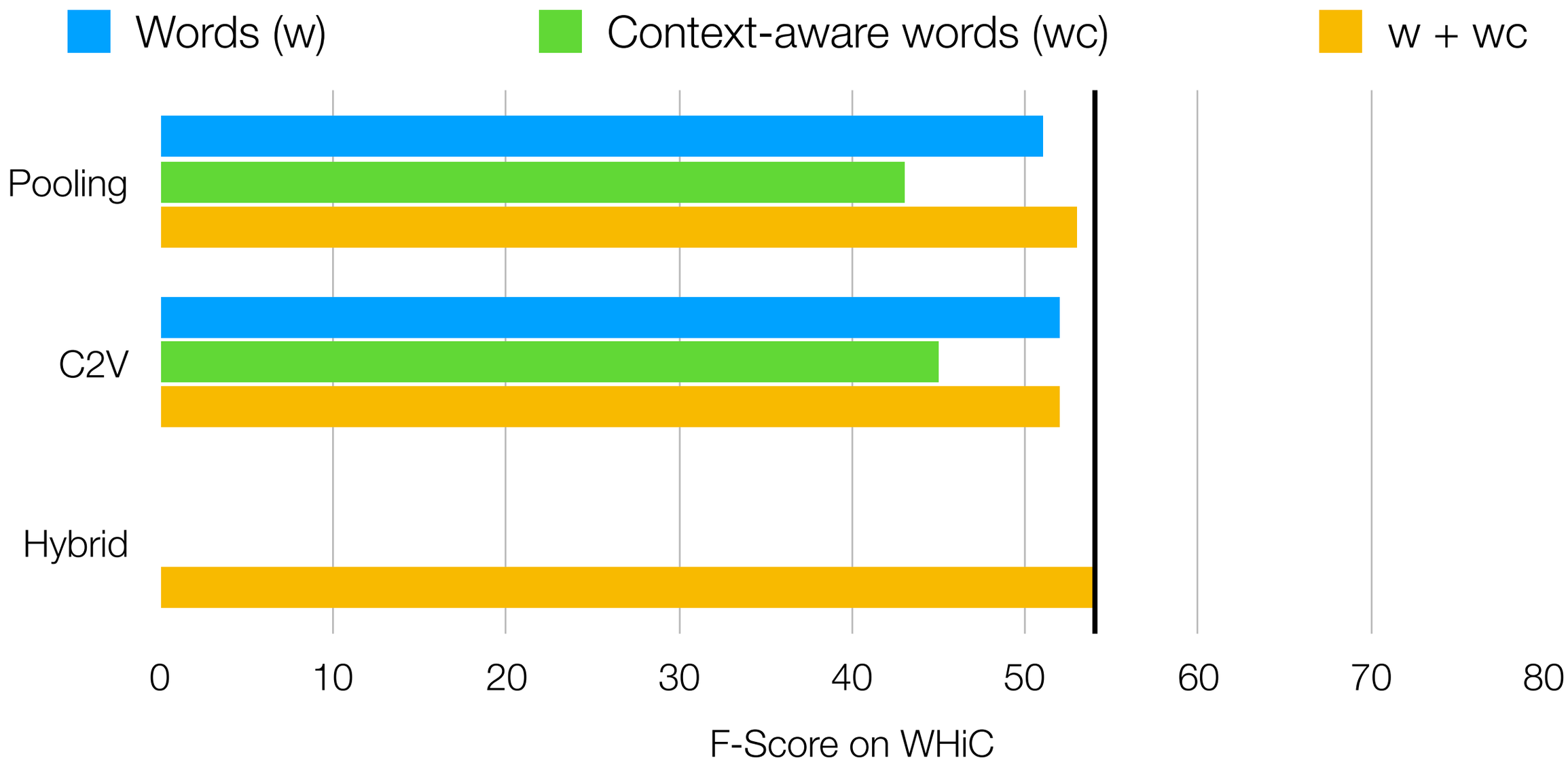

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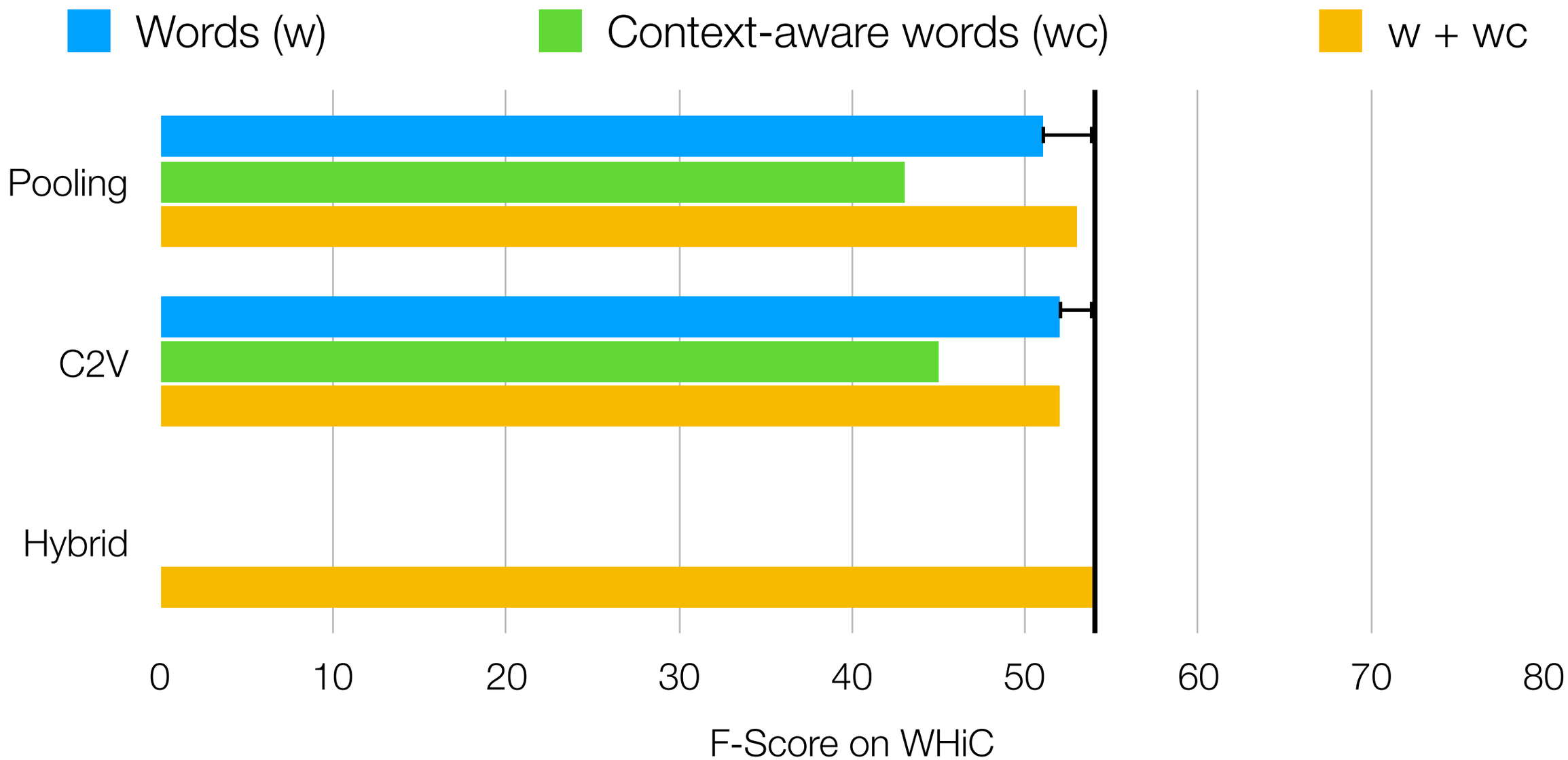
- Context aware representations help ..
- Hybrid model works best



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- Context aware representations help ..
- Hybrid model works best
- Small improvements over context agnostic models

Analysis : Sensitivity to Context

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Word : Room
Example : the rooms were small but comfortable

Word : Study
Example : he knocked on the door of the study

Word : Drawing
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Word : Study
Example : he made several studies before the final painting

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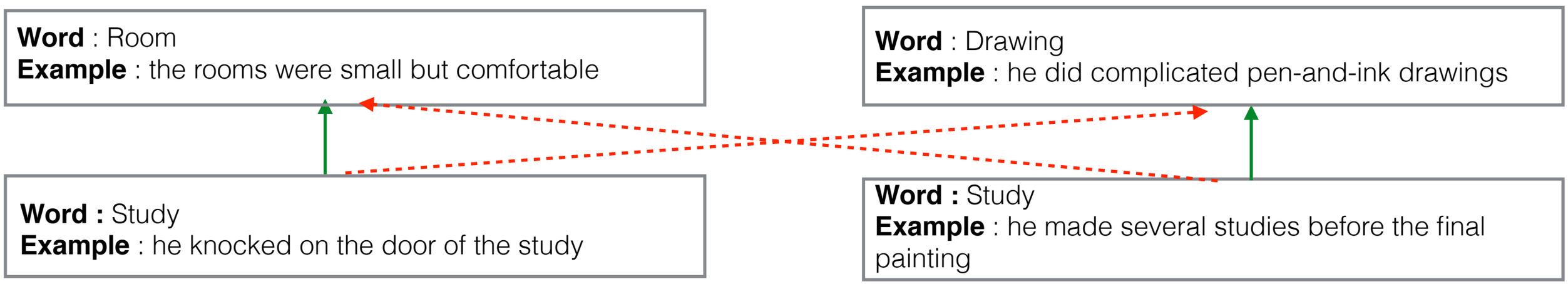

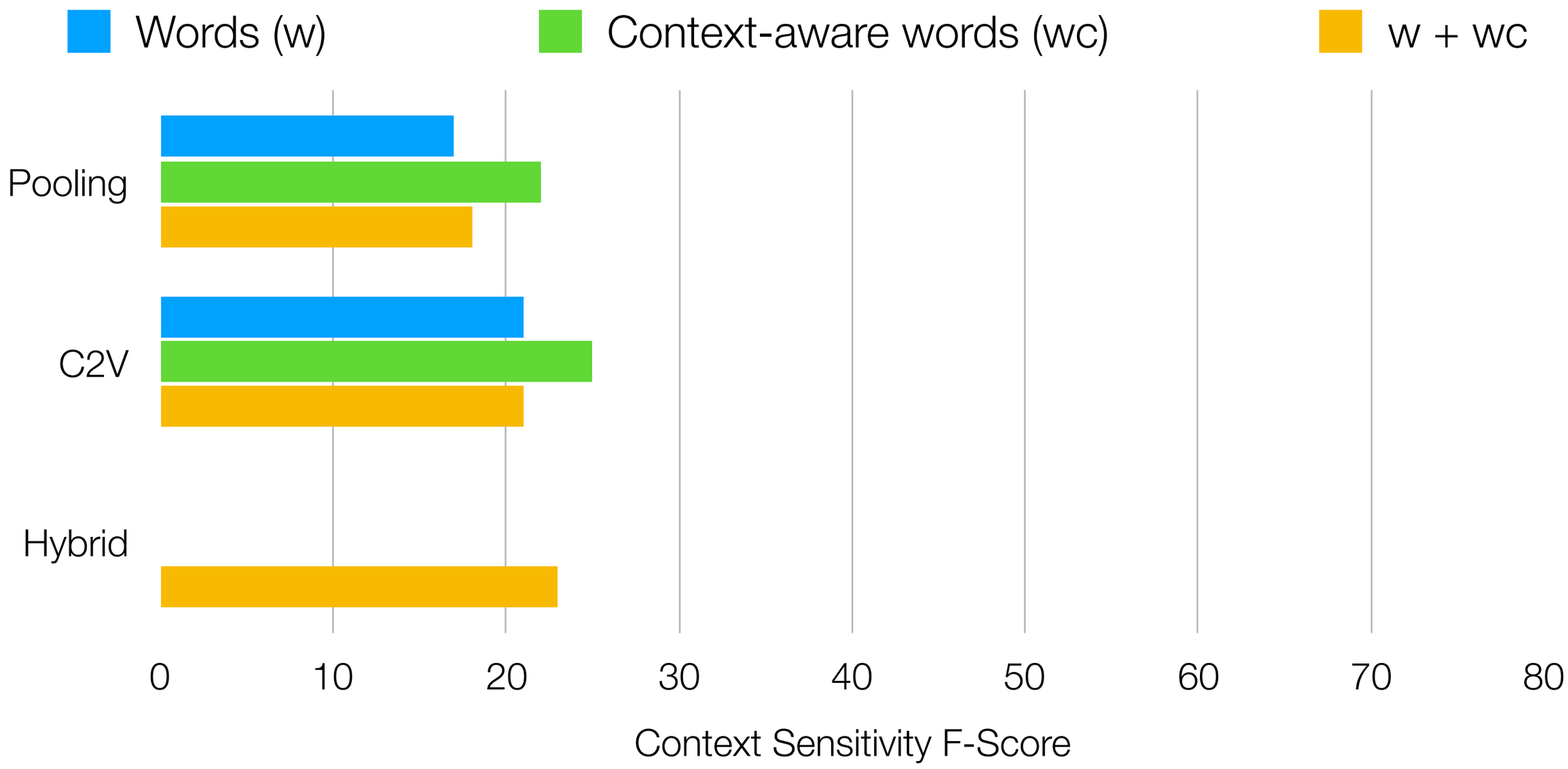
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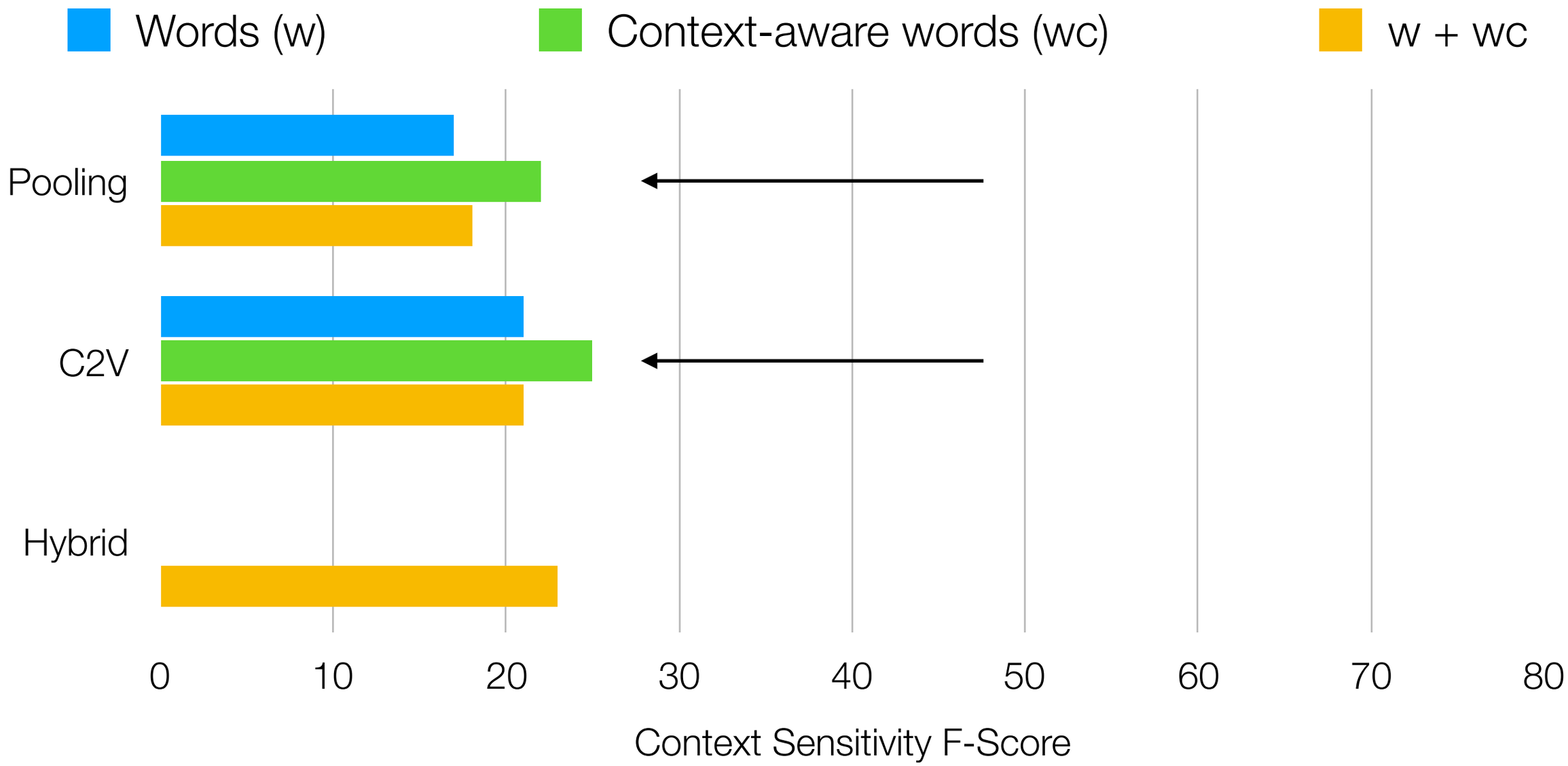
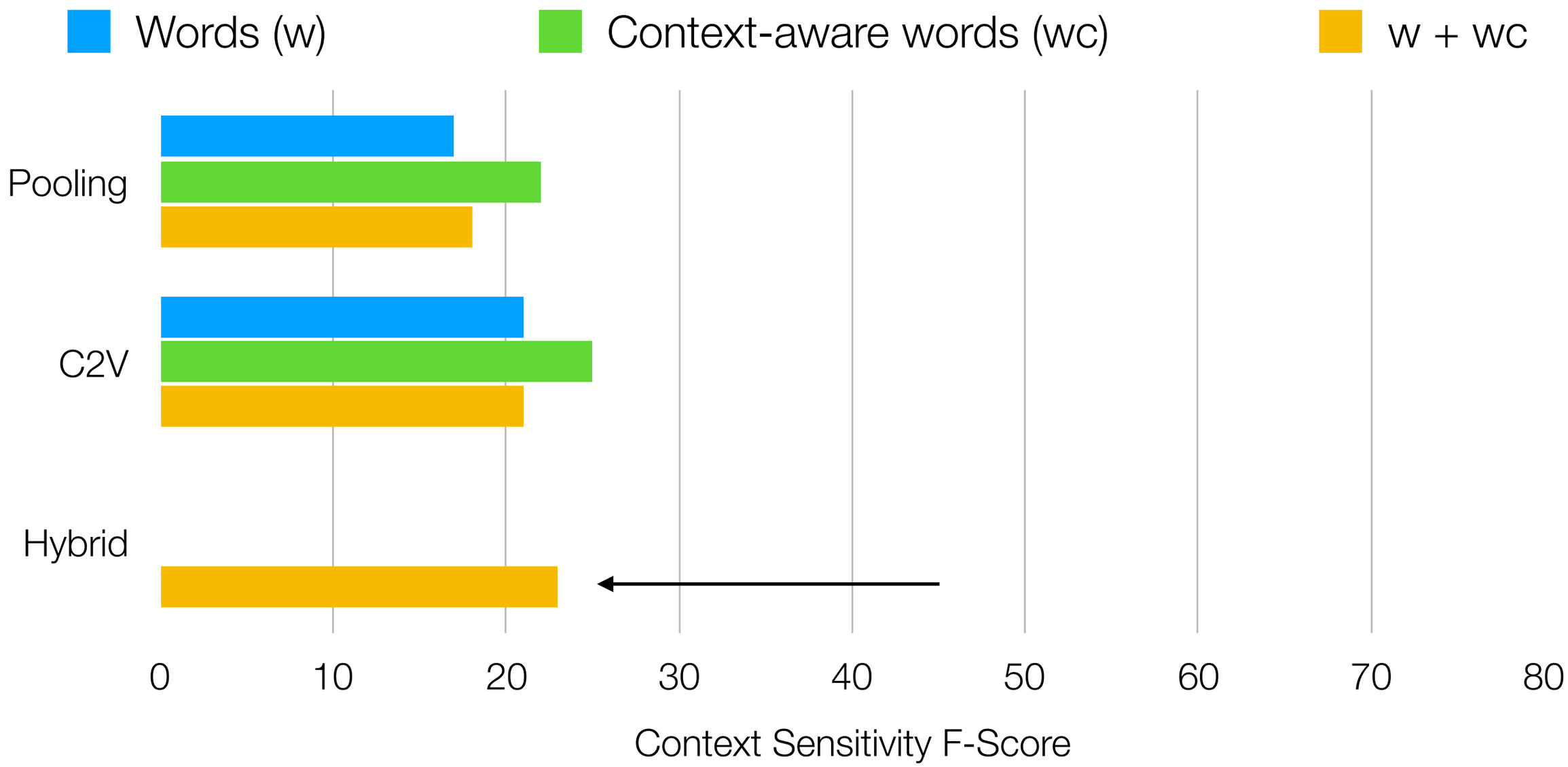


- Context aware representations do better on this subset



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- .. followed by the hybrid model

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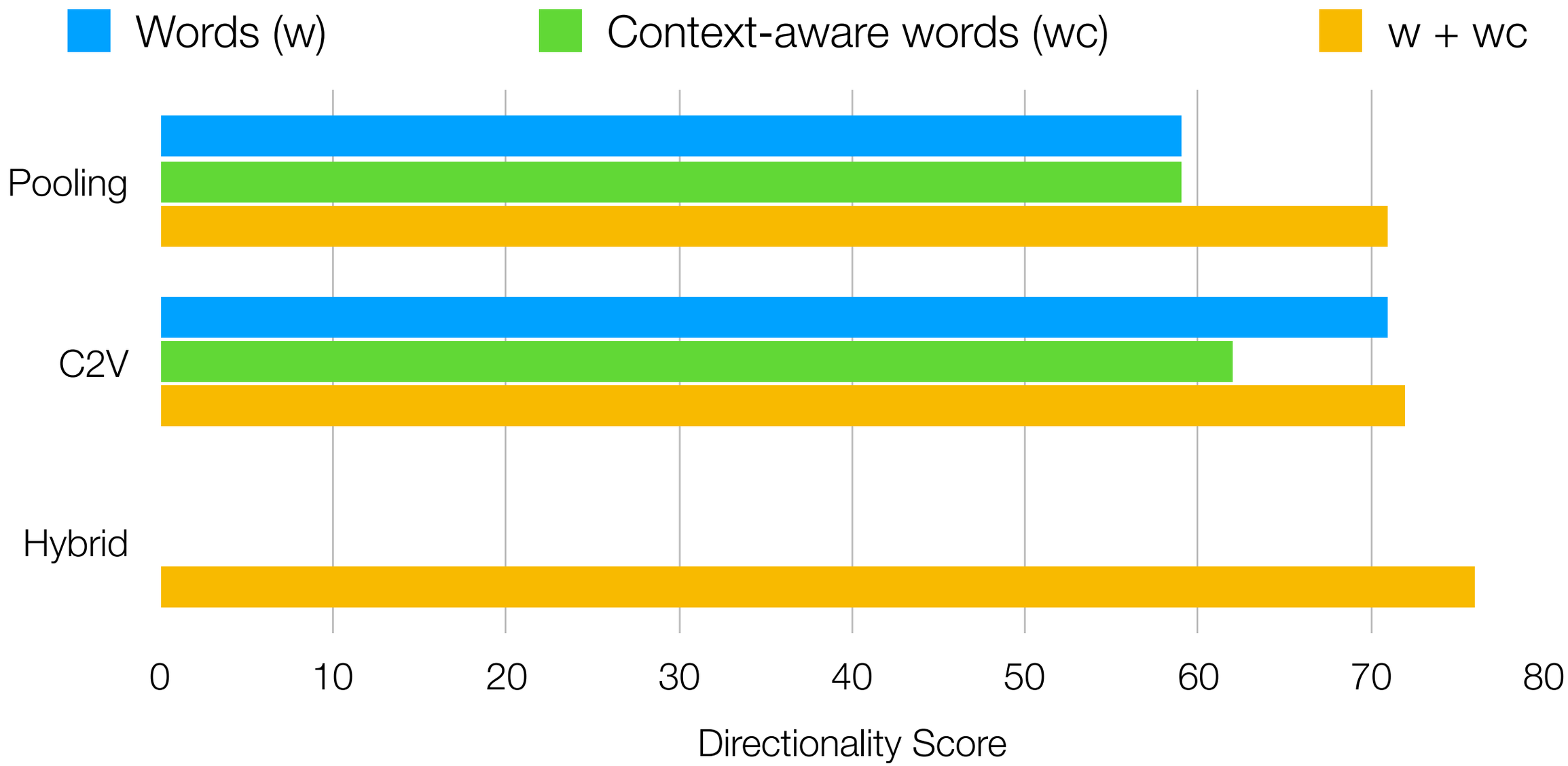
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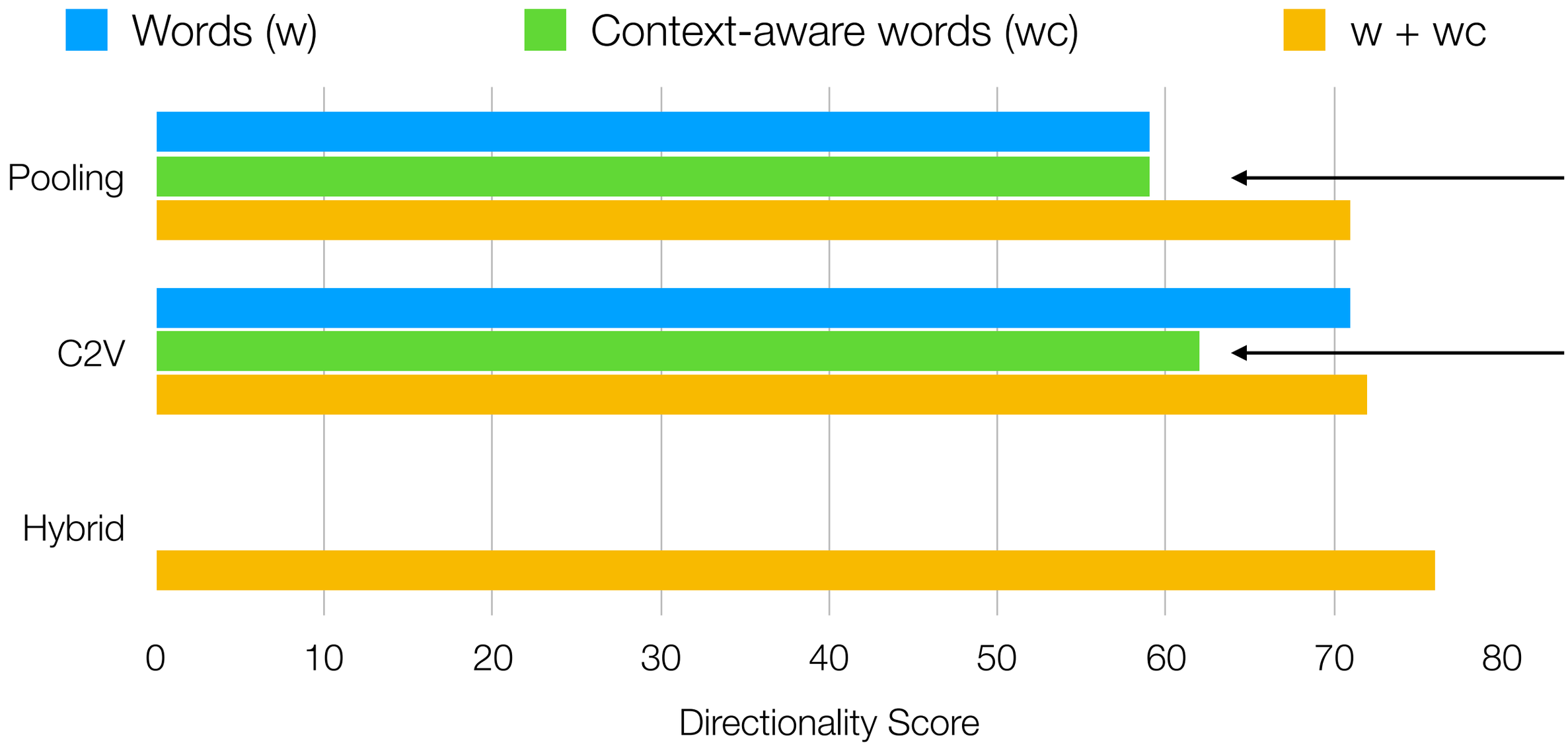

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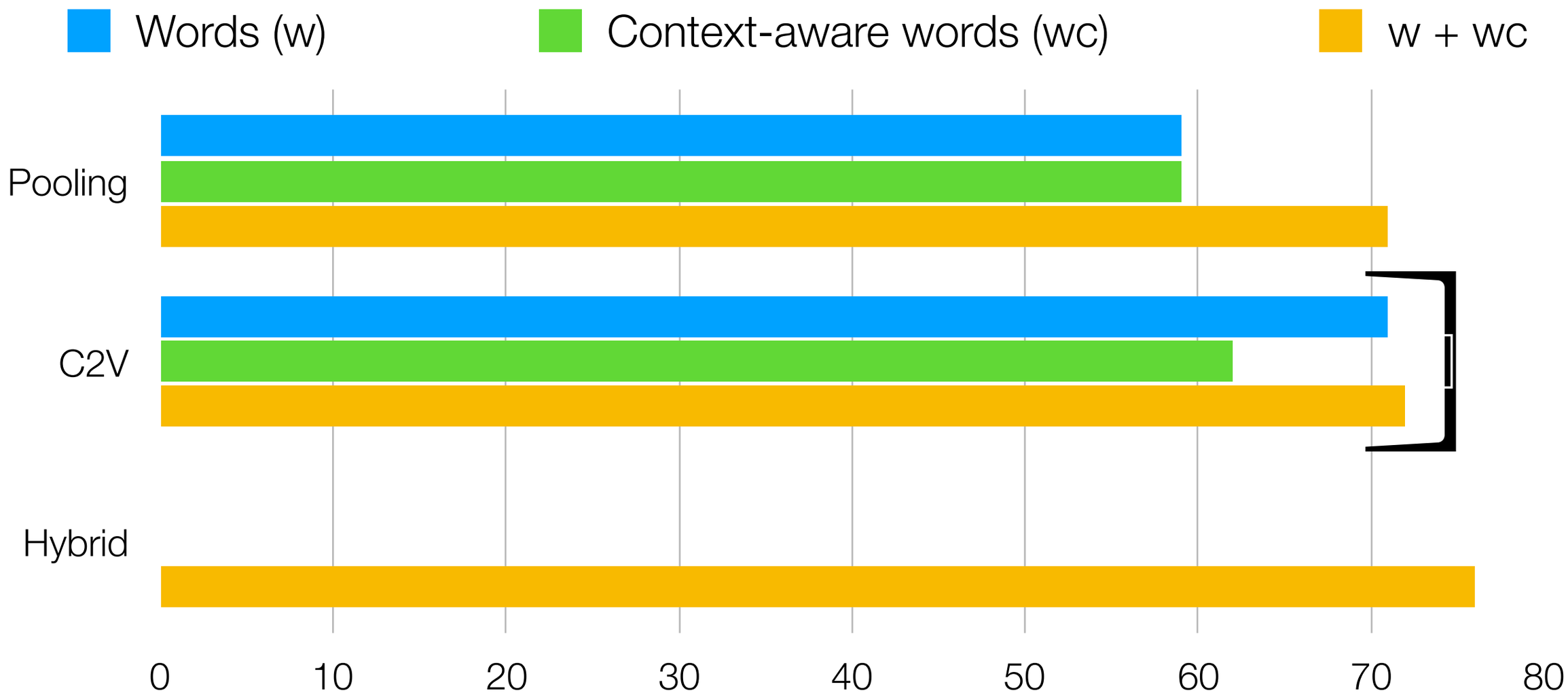
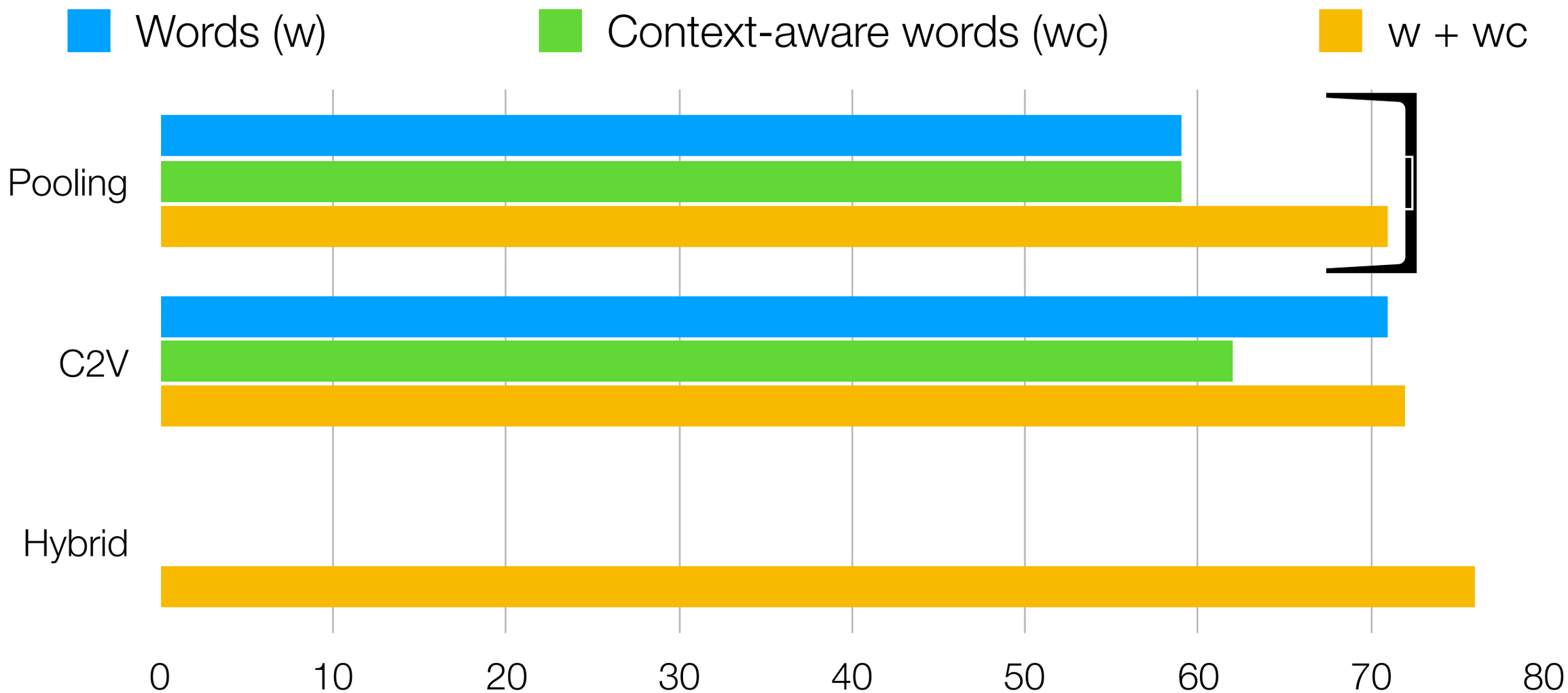


- Context-aware representations do worse
- Context2Vec models are better than Pooling models



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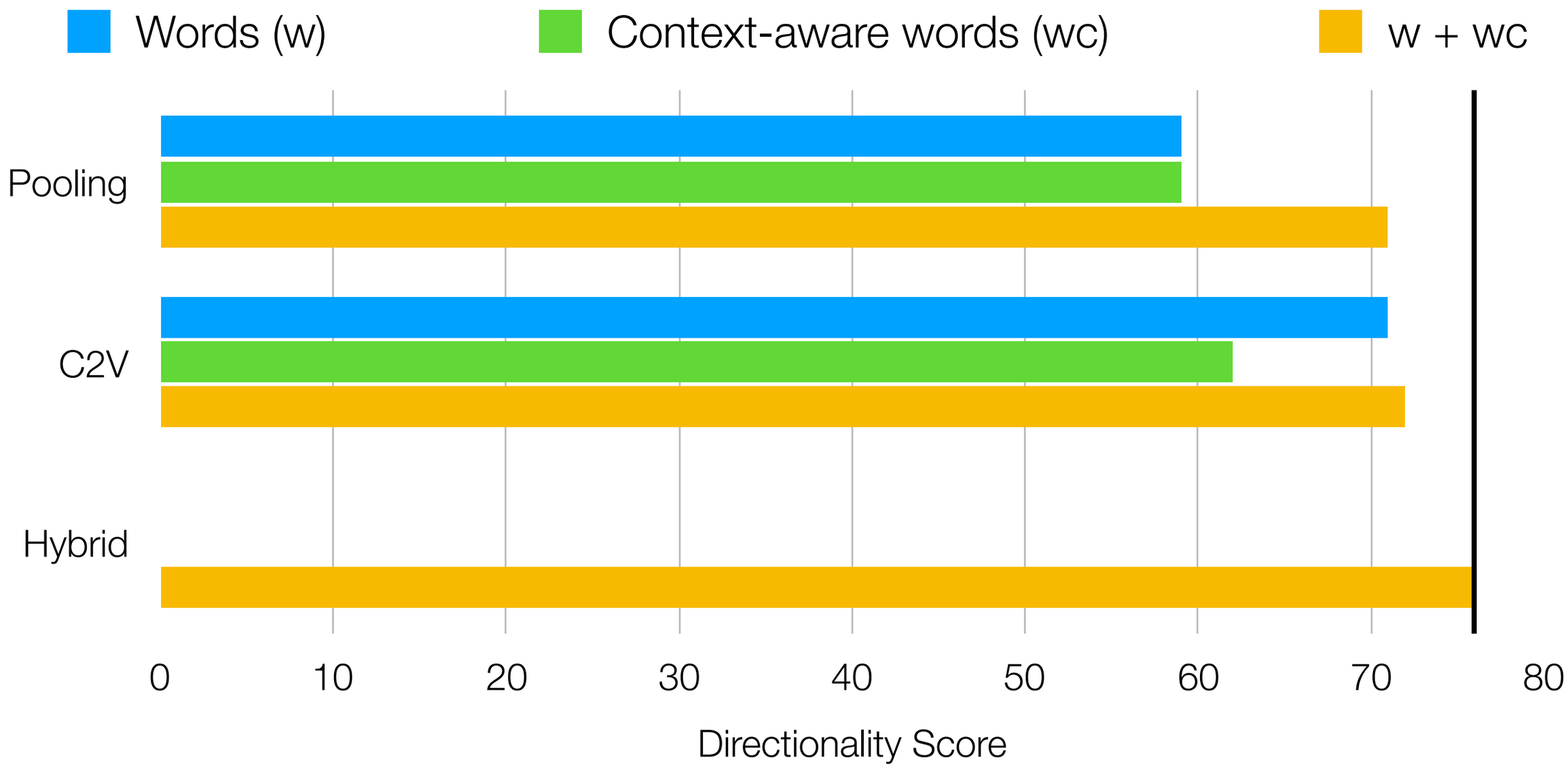

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- Context2Vec models are better than Pooling models
- Hybrid model is best - mirroring performance on the full dataset

Results Summary

- Context aware hypernymy detection is **challenging**!

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- Context aware representations **help** in capturing **context**
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Results Summary

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  - Do **worse** at capturing **asymmetry**
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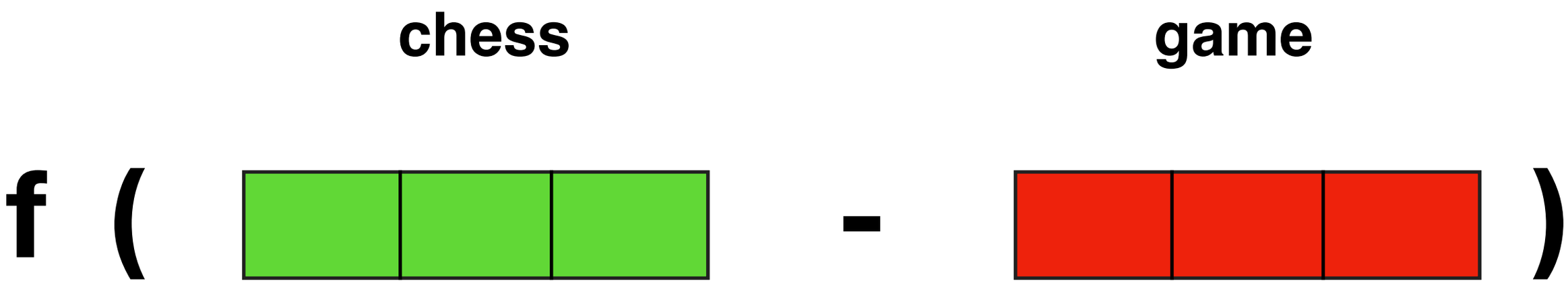
https://github.com/yogarshi/WHiC

Backup

Supervised Hypernymy Detection



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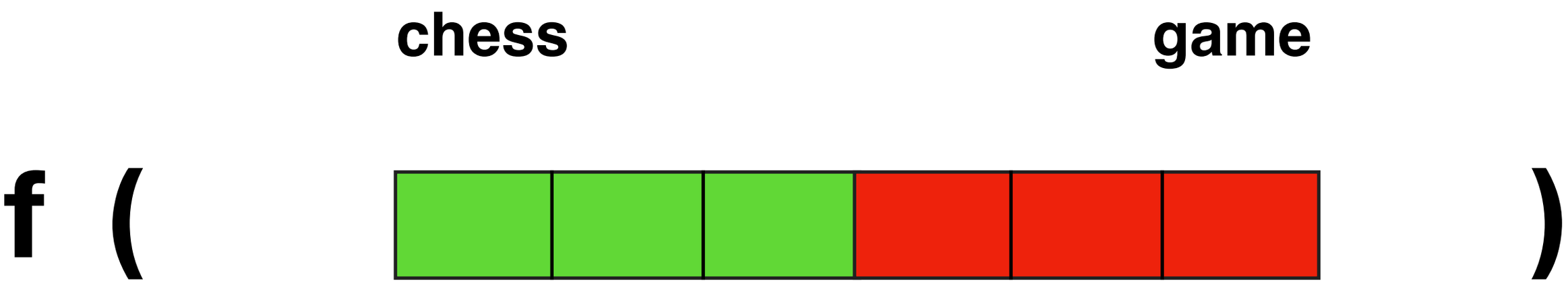

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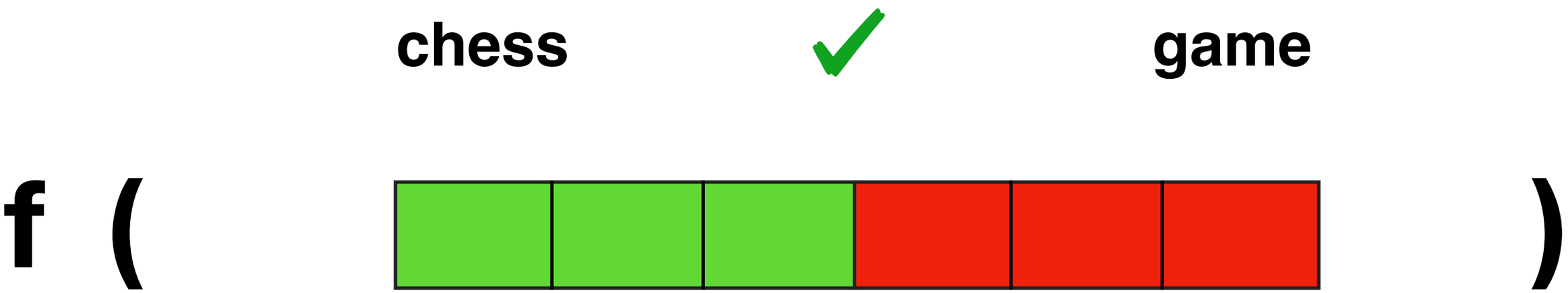
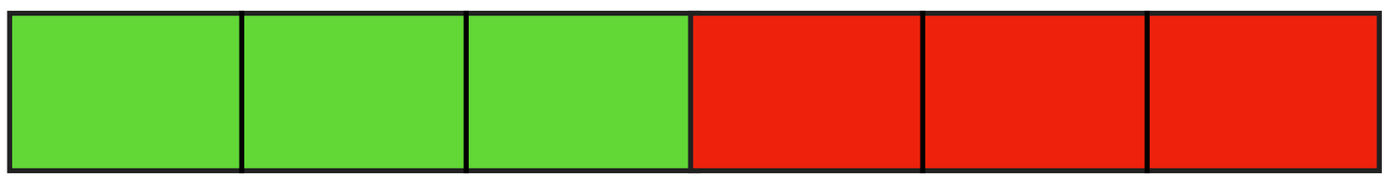


Supervised Hypernymy Detection

dog ✓ **game**

f ( **)**

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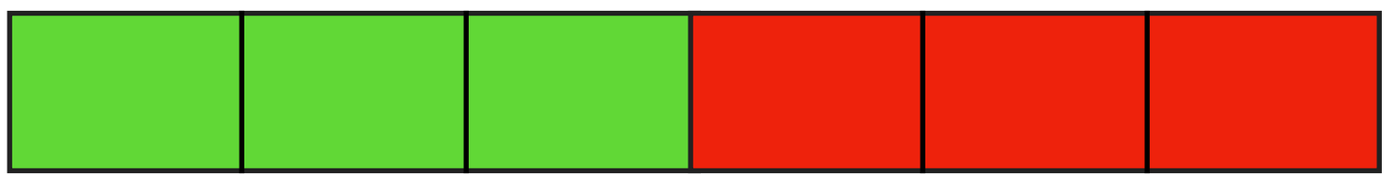
sofa ✓ **game**

f ( **)**

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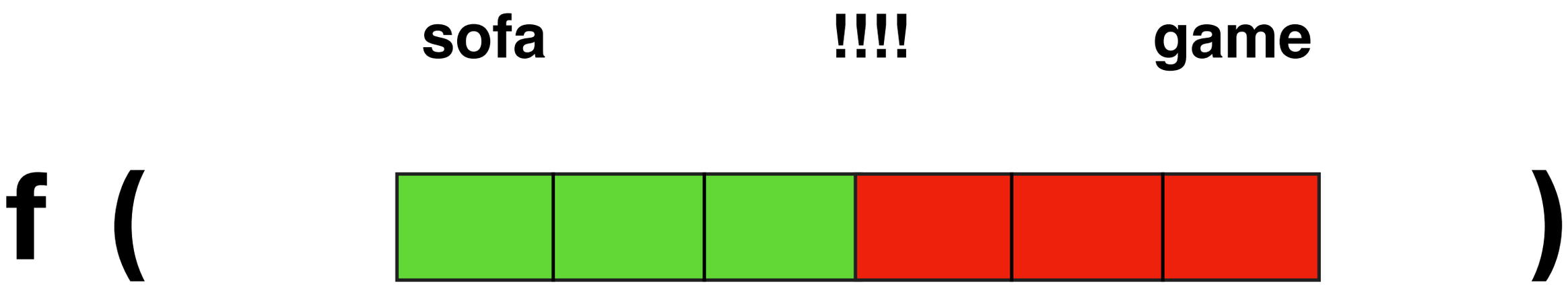

H - Feature Detector

Roller and Erk; EMNLP 2016

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- Project word representations on the plane **orthogonal** to this hyperplane

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→ Non - linear classifier