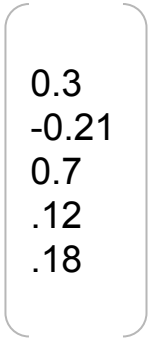
한국어 형태적 특징을 반영한 단어 임베딩 모델(Skipgram, Glove, Fasttext)의 통합적 고찰

-매개변수 조절과 감정분석에 적용한 성능비교

Background

Word Embedding ?

KING =



Analogy ?

King : Queen = Man : ?

? = vec(King) - vec(Queen) + vec(Man)

Similarity?

Top5(Superman)

-> Hero, Batman, Ironman, X-men, Spiderman

Embedding Methods

Prediction Based

Trying to predict the **word** from its **neighbors**

(e.g.) NPLM, skipgram, cbow, fastText ...

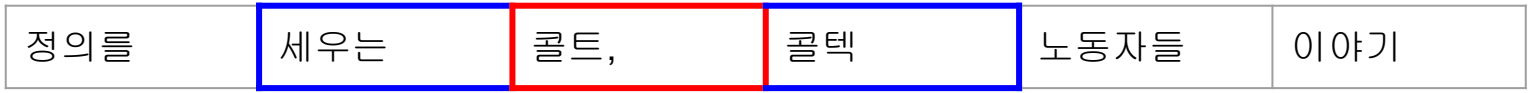
Count Based

How often the same word **co-occurs** with its **neighbor** words in a large text corpus

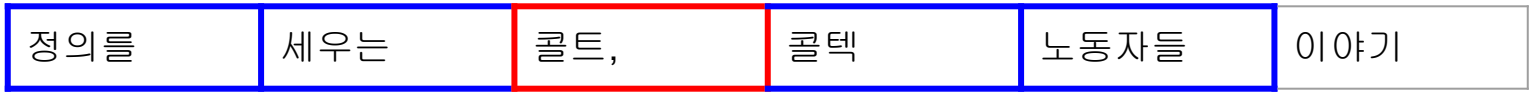
(e.g.) LSA , GloVe ...

Local Context Window

Window size : 1



\Window size :2



Red - Target Word / Blue - Context Word

Collect - D

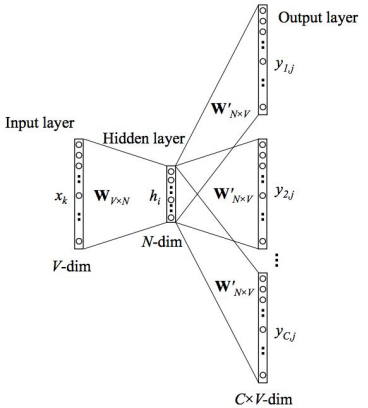
D: All (**word**, **context**) pair in the corpus

Sliding Window (Size=1)	Target Word	Context Word
[정의를 세우는]	정의를	세우는
[정의를 세우는 콜트]	세우는	정의를, 콜트
[세우는 콜트, 콜텍]	콜트	세우는, 콜텍
[콜트, 콜텍, 노동자들]	콜텍	콜트, 노동자들
[콜텍, 노동자들, 이야기]	노동자들	콜텍, 이야기
[노동자들, 이야기]	이야기	노동자들

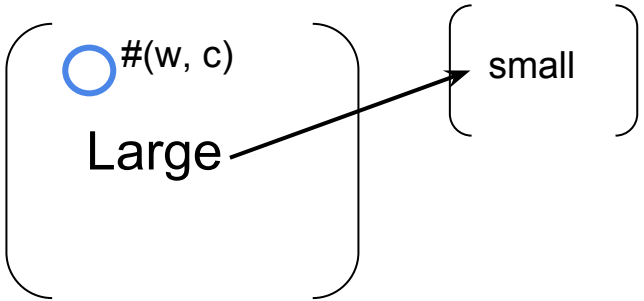
Prediction Based

Given X , Predict Y or

Given Y, Predict X



Count Based



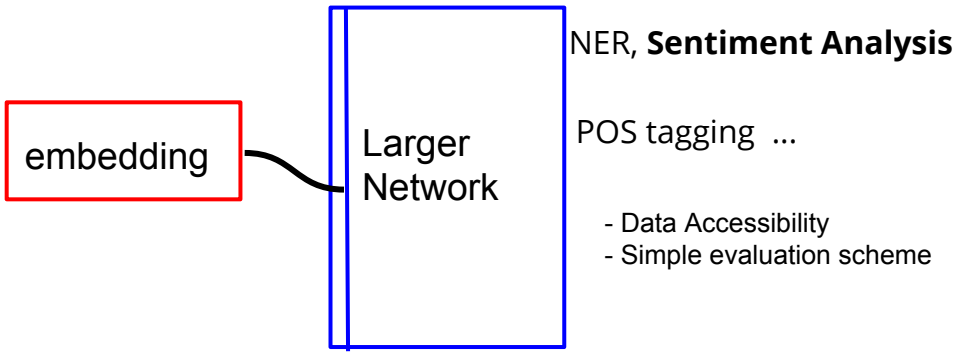
So...?

Evaluation ?

Intrinsic Evaluation : Similarity or Analogy ...

- 성능이 data set 마다 다르게 측정됨

Extrinsic Evaluation : Task Based



Korean ?

Base Input Unit : Word

- 단어당 평균 빈도수가 유지되기 힘듬, 노이즈로 작용

Simple Solution

Word → Morpheme

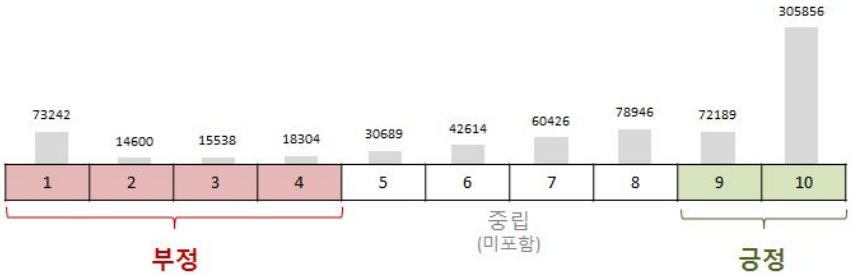
***(+ α* fastText :** *Syllable → Grapheme)*

→ **How to tune parameters?**

DataSet

NSMC(Naver Sentiment Movie Corpus)

- Maas et al., 2011 데이터셋 참고
- 데이터 출처: 네이버
- 영화 당 100개의 140자평(이하 '리뷰')을 초과하지 않음
- 총 20만 개 리뷰 (수집된 64만개 중 샘플링)
    - ratings_train.txt: 15만, ratings_test.txt: 5만
    - 긍정/부정 리뷰의 비율을 동일하게 샘플링 (i.e., random guess yields 50% accuracy)
    - 중립 리뷰는 포함하지 않음



Movie Review Example

Id	Document	Label
8112052	어릴때보고 지금다시봐도 재밌어요ㅋㅋ	1
9125596	가면갈수록 내용이 개판이다. 많은걸 집어넣으려다망함	0

Experiment?

Step 1 — Create Embedding

Step 2 — Create Training Samples

Step 3 — Define Network

Step 4 — Train & Validate

1. Create Embeddings

Input Unit

모델 / 입력단위	CBOW	SkipGram	Glove	FastText	
				음절	자음,모음(grapheme)
단어	["그는", "학생이다"]			[["그","는"], ["학","생","이","다"]	[["ㄱ, ㅡ, ㄴ", "ㄴ,ㅡ,ㄴ"], ["ㅎ","ㅏ","ㄱ"...]
형태소	["그", "는", "학생", "이다"]			[["그"], ["는"], [["학","생"], [["이","다"]]]	[["ㄱ, ㅡ, ㄴ", "ㄴ,ㅡ,ㄴ"], ["ㅎ","ㅏ","ㄱ"...]

*Morpheme Analysis : **Twitter** Morpheme Analyzer

Parameter

Dimension Size : 50 , 100 ,300, 500, 1000
Window : 2, 5, 7, 10
Minimum count : 10, 20, 50, 100

_____
Others : Default

Parameter Variation * # Input Variation + # partial result
= 80 * 8 + **α**

Experiment?

Step 1 — Create Embedding

Step 2 — Create Training Samples

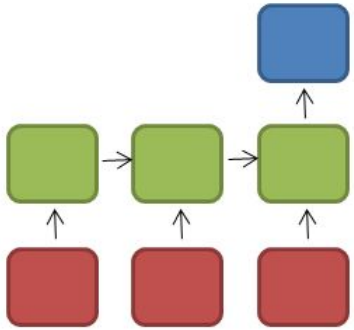
Step 3 — **Define Network**

Step 4 — **Train & Validate**

2. Create Training Samples

(1)	K_{word}^{raw}	['아', '더빙', '진짜', '짜증', '나네', '요', '목소리']
(2)	$K_{word}^{integer}$	[182, 132, 22, 17, 98, 16, 52]
(3)	K_{word}^{1-hot}	[[0,0,0,0,0,...1,0,0,0],[0,0,0,0,0,...,1,0,0] ...]
(4)	zero_padding(K_{word}^{1-hot})	[[0,0,0,0,0,...1,0,0,0],[0,0,0,0,0,...,1,0,0] ... **[0,0, ...,0,]**]
(5)	labels – 1hot encoding	[[0, 1]], [1, 0] ...]

3. Define Network



Dense layer

LSTM Layer

Embedding Layer

Experiment?

Step 1 — Create Embedding

Step 2 — Create Training Samples

Step 3 — Define Network

Step 4 — **Train & Validate**

4. Train & Validate

- # training : 15k, validation : 5k
- batch size : 128
- maximum epoch : 20
- Early Stopping: patience 5
- Optimizer : Adam(Adaptive Moment Estimation)
- Loss : Binary Crossentrophy

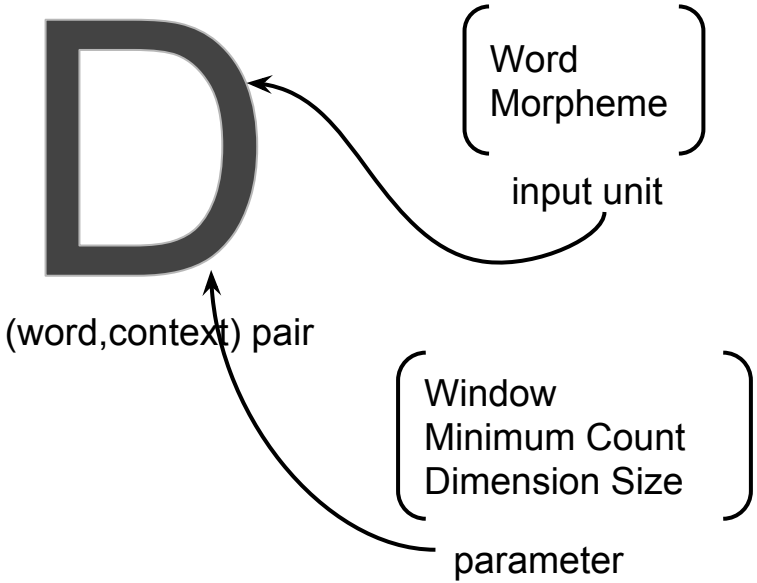
Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 50)	0
embedding_1 (Embedding)	(None, 50, 300)	88354800
lstm_1 (LSTM)	(None, 300)	721200
dense_1 (Dense)	(None, 2)	602

Total params: 89,076,602
Trainable params: 721,802
Non-trainable params: 88,354,800

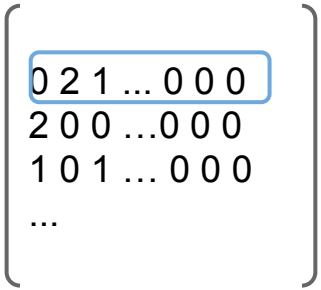
Optimizer: adam, Loss : binary_crossentropy, EarlyStopping : 5 (patience level)

How to Interpret Result ?

Src of information



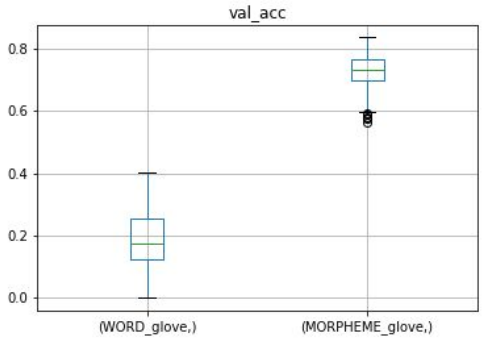
Co-occurence matrix



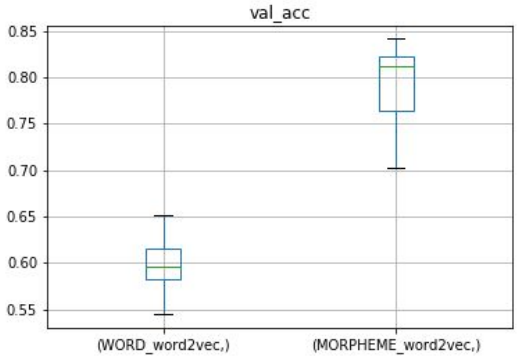
- # of vocabulary
- # of average freq
- # of average non zero columns

Result - Input Unit

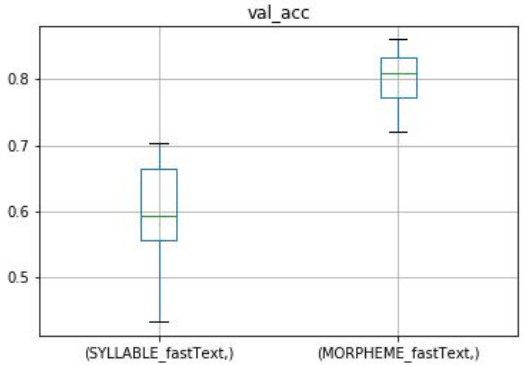
Glove



Skipgram



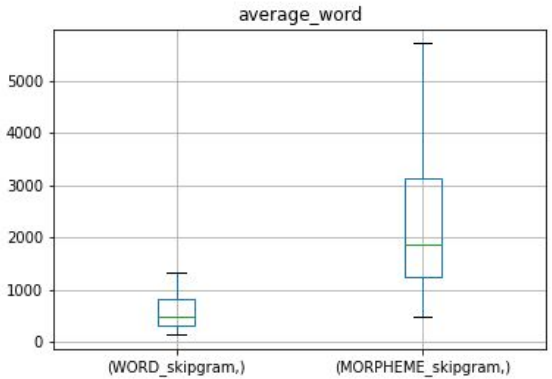
FastText_Syllable



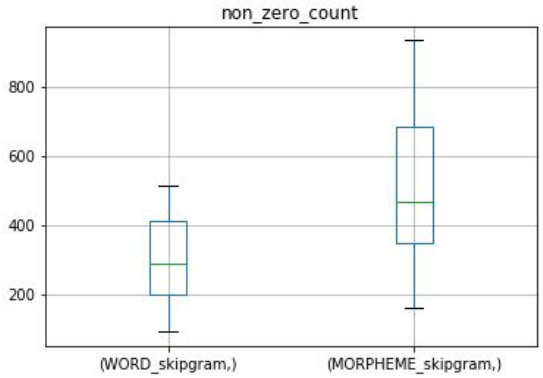
- 모든 모델에서 형태소 단위의 입력이 성능이 더 좋음

Result - Interpretation

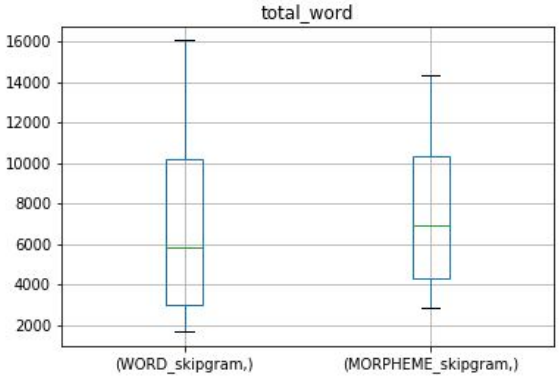
어휘당 평균 출현빈도



어휘당 문맥의 종류



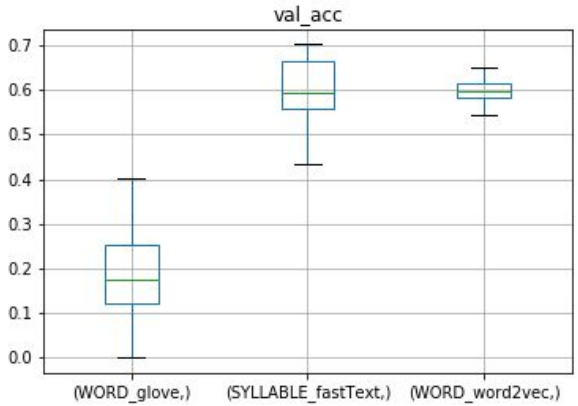
전체 단어 종류



- 전체 단어종류는 줄어들었지만,
- 어휘당 평균 출현빈도와 문맥의 종류는 증가했다

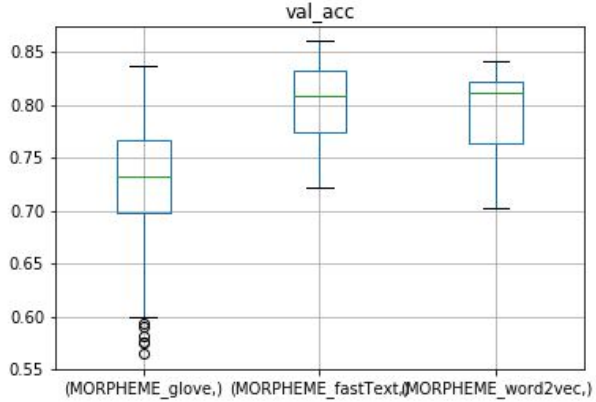
Result - between models

Word



- Glove < Skipgram < FastText

MORPHEME



- Glove < Skipgram < FastText

Result Interpretation

Tianze Shi and Ahiyuan Liu(2014)

- Bias term 간에 강한 연관
- SGNS가 최적화 하는 행렬과 Glove가 비슷

	Glove	Skipgram with Negative Sampling
Local cost function	$l_G(w_i, c_j) = f(X_{i,j}) \times \left(W_i \cdot C_j^T + b_{w_i} + b_{c_j} - \log X_{i,j}\right)$ $f(x) = \begin{cases} \left(\frac{x}{x_{max}}\right)^{\alpha}, & x < x_{max} \\ 1, & otherwise \end{cases}$ $X_{i,j} = \#(w_i, c_j)$ $\alpha = \frac{3}{4}, \quad x_{max} = 100$	$l_s(w_i, c_j) = X_{i,j} \times log\sigma(W_i \cdot C_j^T) + k \times \#(w_i) \cdot \frac{\#(c_j)}{\sum_w \#w} log\sigma(-(W_i \cdot C_j^T))$
Global cost function	$\sum_{i=1}^{\lvert V_W \rvert} \sum_{j=1}^{\lvert V_C \rvert} l_G(w_i, c_j)$	$\sum_{i=1}^{\lvert V_W \rvert} \sum_{j=1}^{\lvert V_C \rvert} l_s(w_i, c_j)$
$M = W_i \cdot C_j^T$	$W_i \cdot C_j^T = X_{i,j} - b_{w_i} - b_{c_j}$	$W_i \cdot C_j^T = \text{PMI}(w_i, c_j) - logk$ $= X_{i,j} - \log \#(w_i) - \log \#(c_j) + \log \sum_w \#(w) - logk$
Window Weighting Scheme	L = Maximum window size , d = disance from the focus word	
	$\frac{L - d + 1}{L}$	$\frac{L - \sqrt{d} + 1}{L}$

단어-문맥쌍 복원 비용

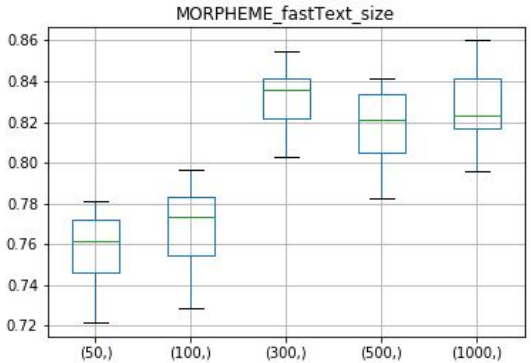
$l(w_i, c_j)$

어휘당 평균 출현 빈도가 확보되지 않았을때 더 큰 영향

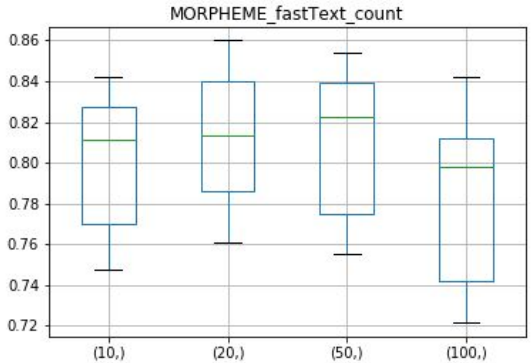
→두 모델간 단어 단위 성능 차이설명

Result - parameter

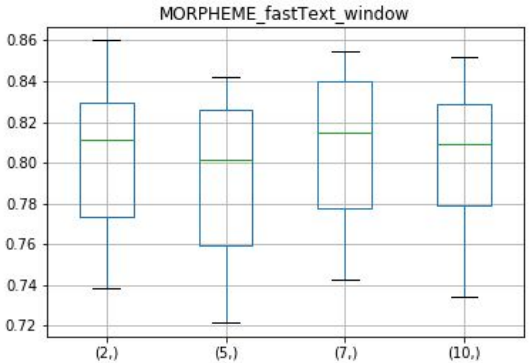
Dimension Size



Minimum Count

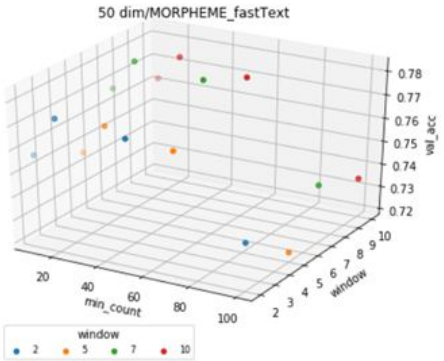


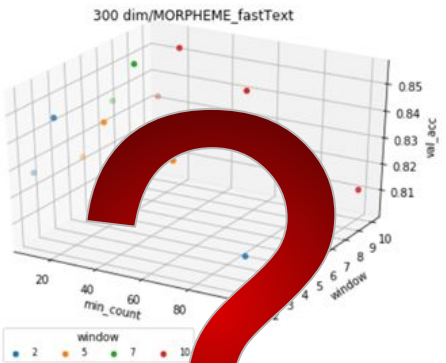
Window Size

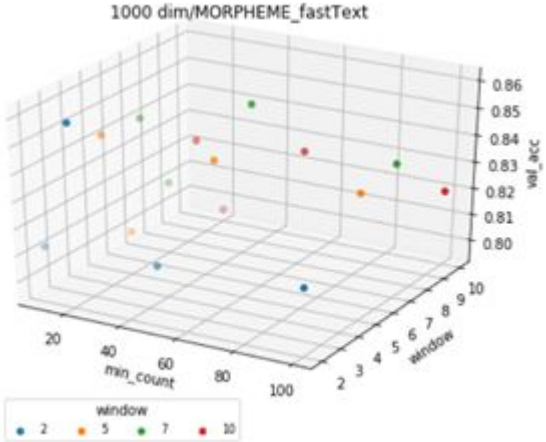


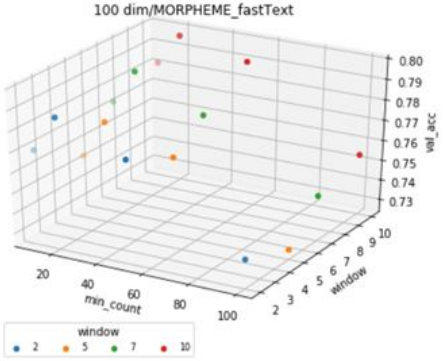
- size파라메터가 모델의 정확도에 가장 영향을 많이주었다
- window, minimum count 중 성능에 더 큰 영향을 주는 요소는?

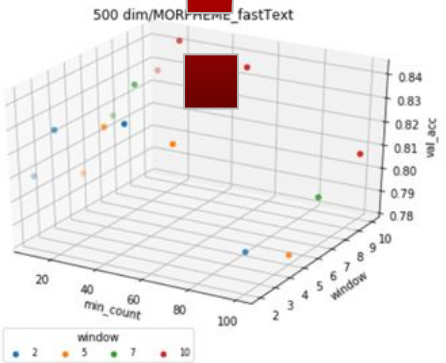
Window - Min Count Relation



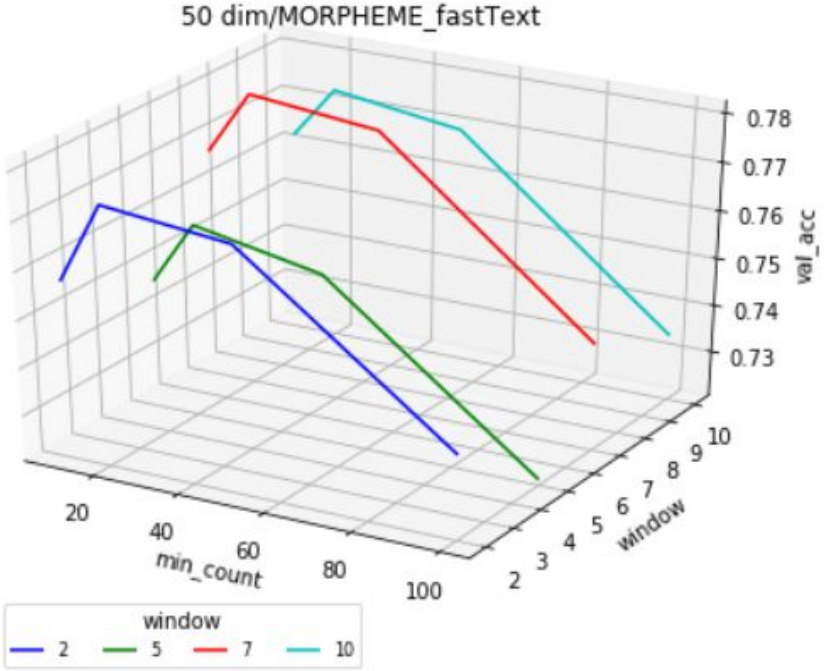








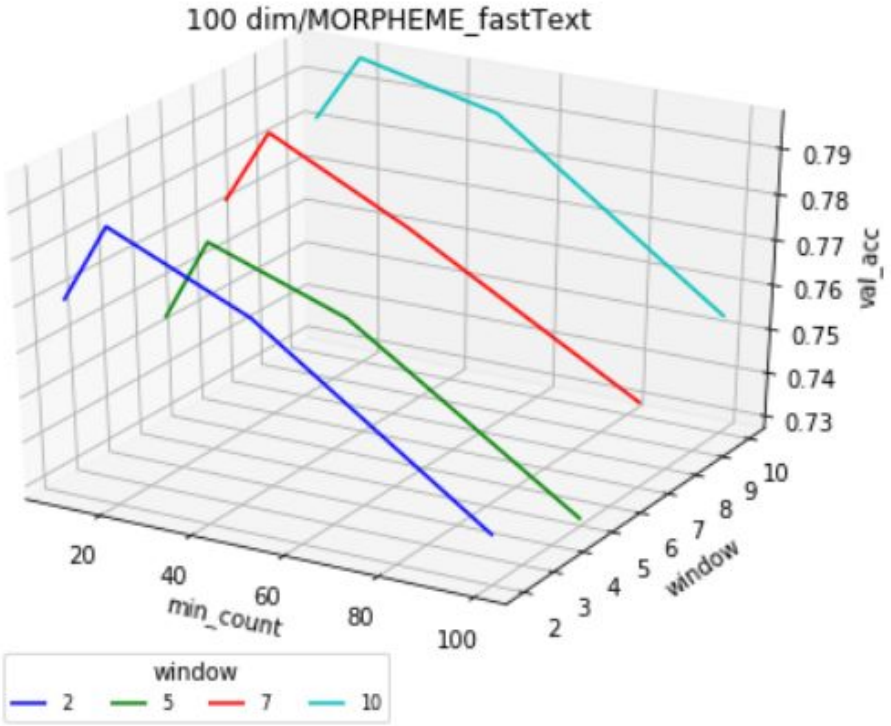
Result - Group By Window



Min Count

50 : [100 10 50 20]
100 : [100 10 50 20]
300 : [100 10 50 20]
500 : [100 10 50 20]
1000 : [100 10 50 20]

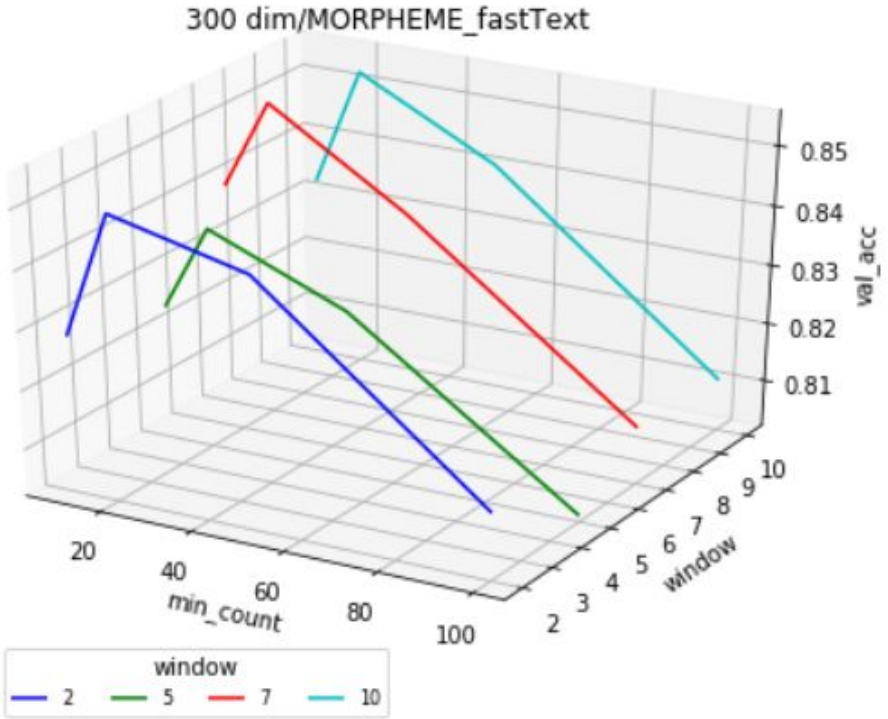
Result - Group By Window



Min Count

50 : [100 10 50 20]
100 : [100 10 50 20]
300 : [100 10 50 20]
500 : [100 10 50 20]
1000 : [100 10 50 20]

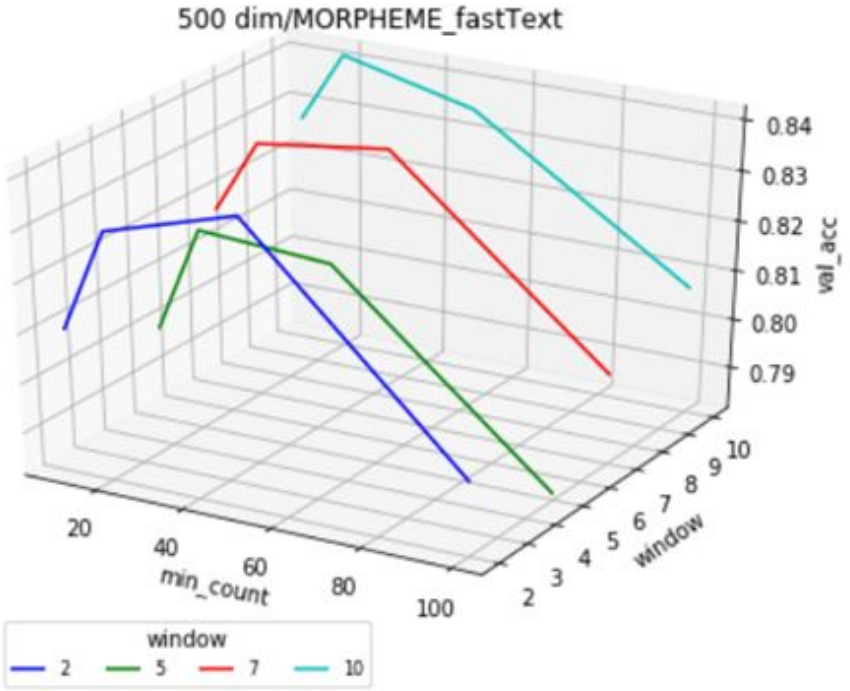
Result - Group By Window



Min Count

50 : [100 10 50 20]
100 : [100 10 50 20]
300 : [100 10 50 20]
500 : [100 10 50 20]
1000 : [100 10 50 20]

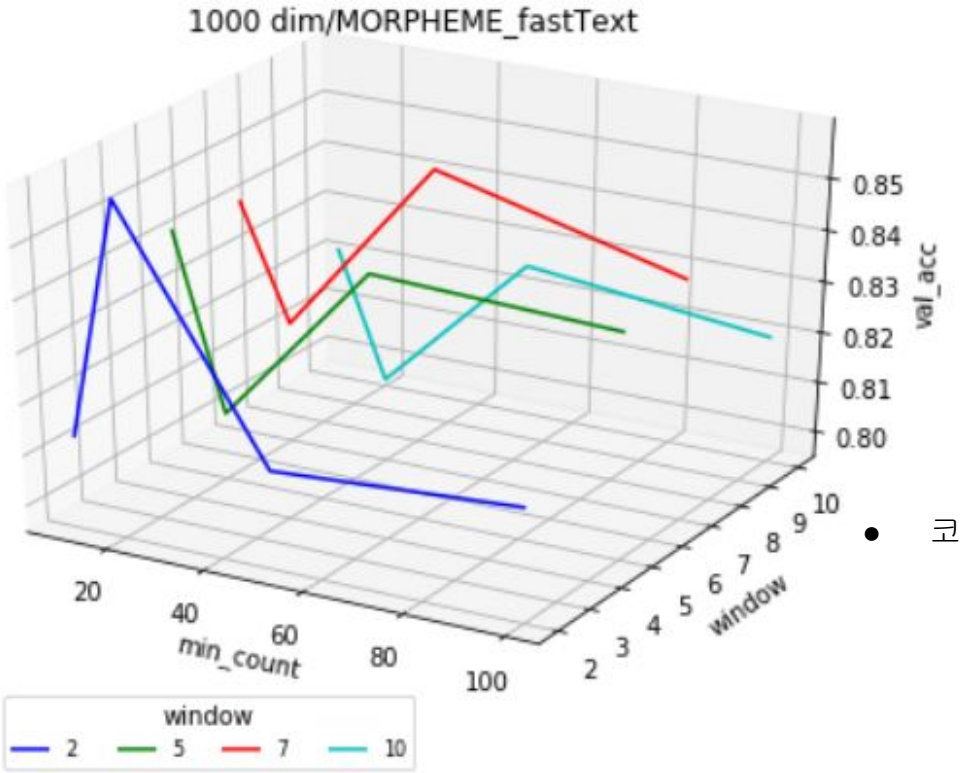
Result - Group By Window



Min Count

50 : [100 10 50 20]
100 : [100 10 50 20]
300 : [100 10 50 20]
500 : [100 10 50 20]
1000 : [100 10 50 20]

Result - Group By Window

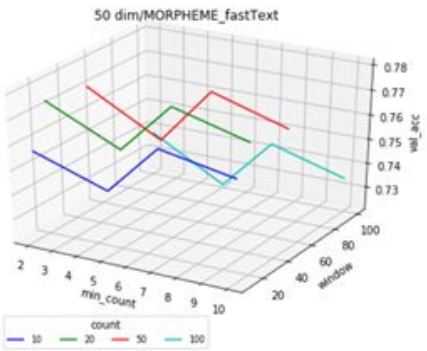


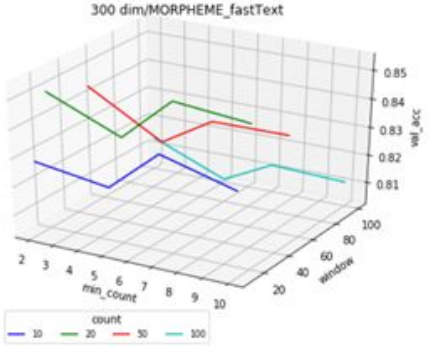
Min Count

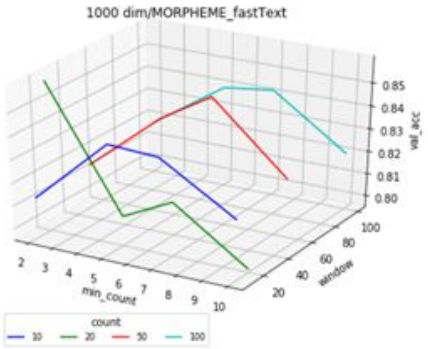
50 : [100 10 50 20]
100 : [100 10 50 20]
300 : [100 10 50 20]
500 : [100 10 50 20]
1000 : [100 10 50 20]

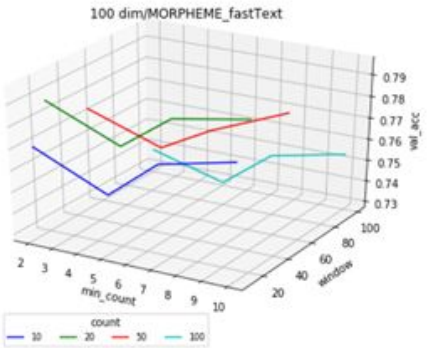
- 코퍼스마다 적정선의 최소출현빈도 파라메터가 존재

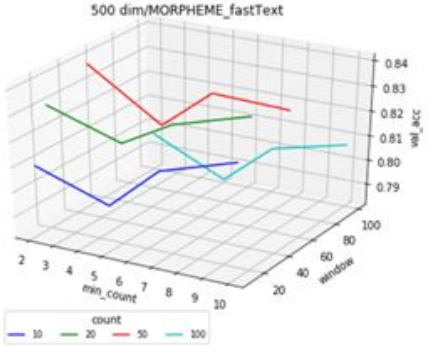
Result - Group By Min Count











Window

50 : [5 10 2 7]

100 : [5 2 7 10]

300 : [5 2 10 7]

500 : [5 7 2 10]

1000 : [10 5 7 2]

Result Interpretation

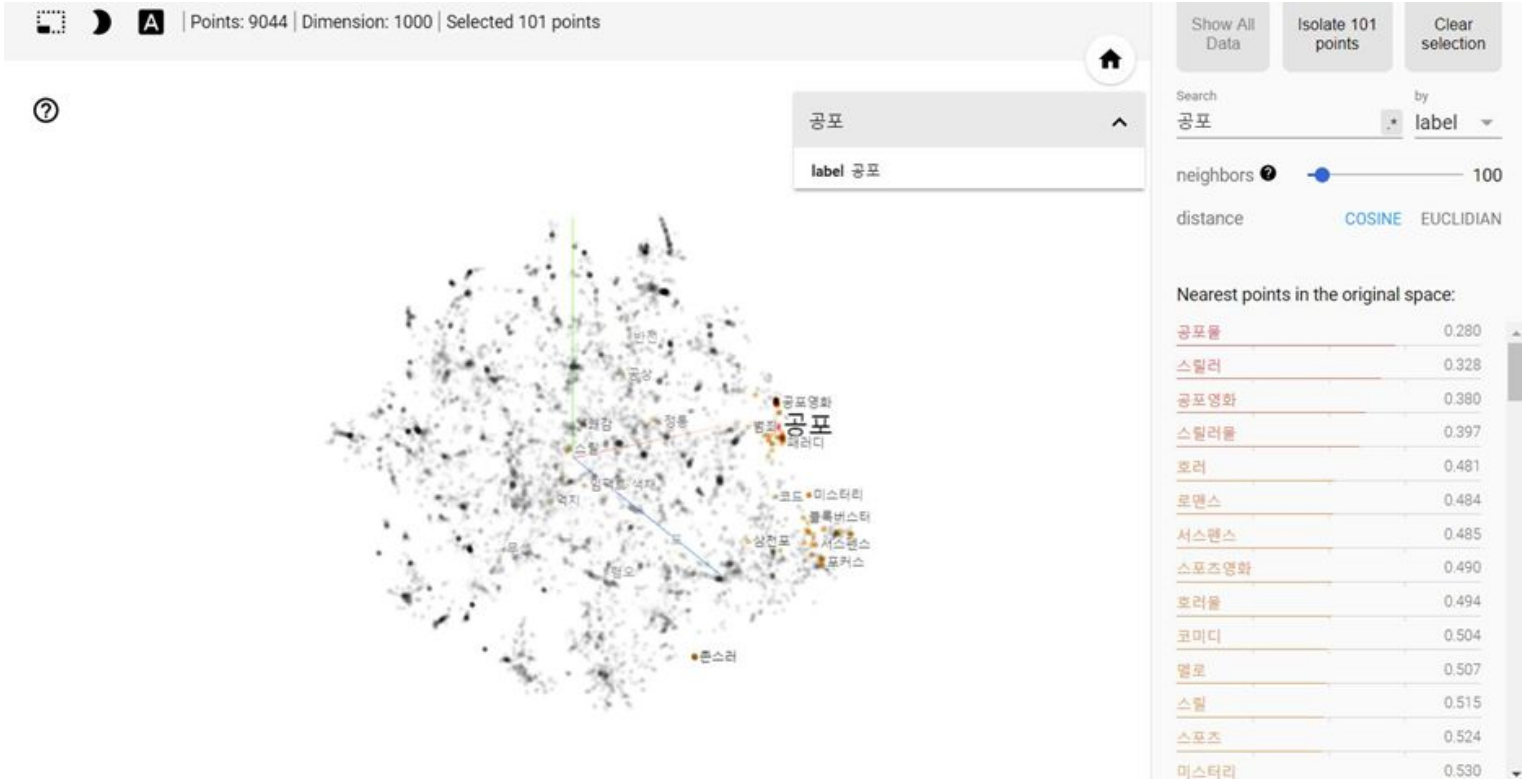
	FastText	Skipgram
출력층의 softmax 계산	$p(c\|w) = \frac{e^{s(c\|w)}}{\sum_{j=1}^{V_W} e^{s(c\|w)}}$	
s(c, w)	$s(c, w) = \sum_{g \in g_w} z_g^T C_c$	$s(c, w) = W_w * C_c$
Ex) 소프트웨어[7] , n=3	g_w 소프트웨어 = { < 소프, 소프트, 프트웨, 트웨어, 웨어 >, < 소프트웨어 >}	W^w 소프트웨어 = <소프트웨어>

fastText 모델에 따르면 target word와 gram을 공유하는 단어의 벡터도 변하기때문에
원래의 윈도우에 포함되어 있지 않은 단어일지라도 학습가능하다.

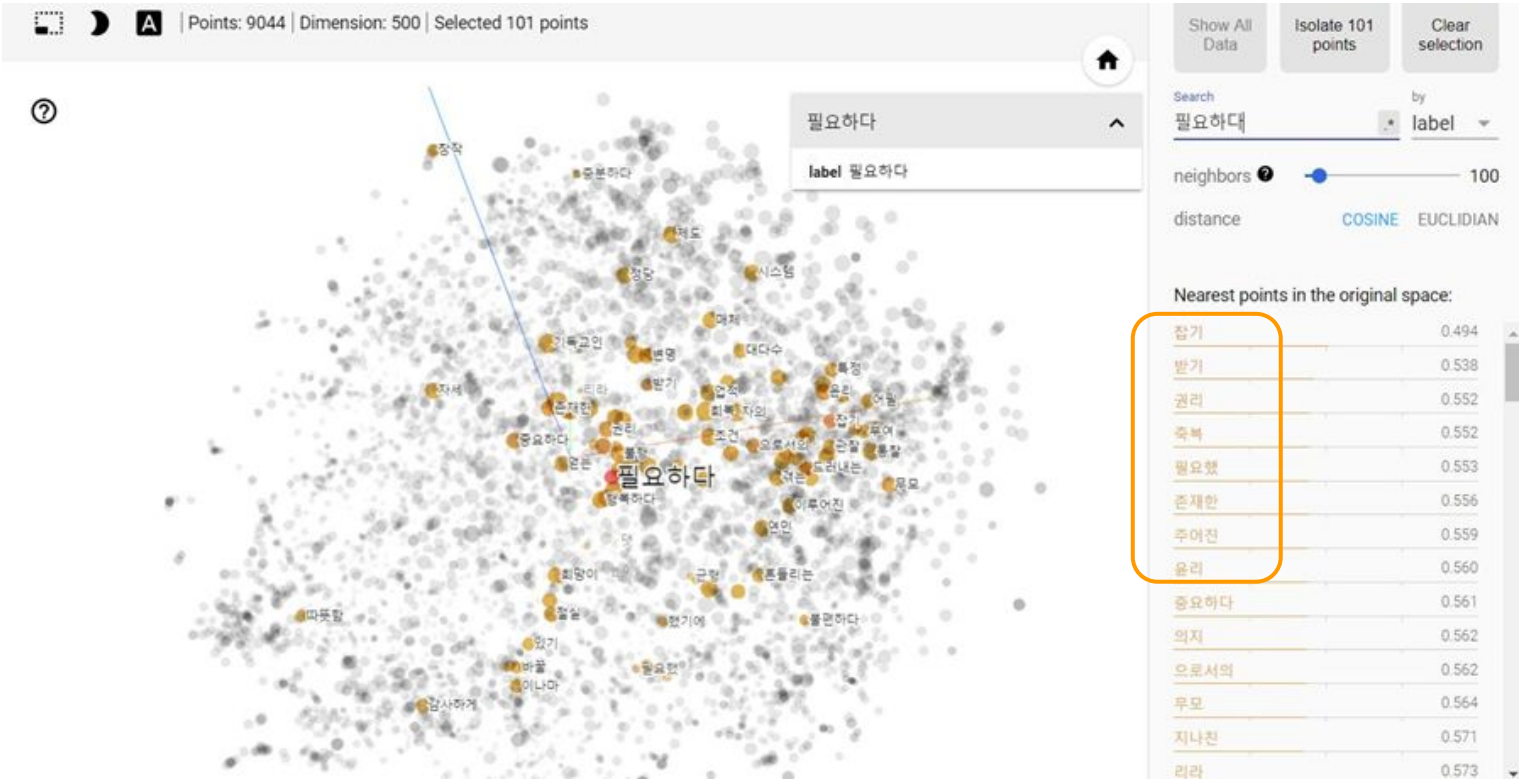
Result Interpretation - PCA

텐서보드의 Embedding Projector에 맵핑을 하였고,¶
PCA 보다는 TSNE의 클러스터가 두 모델간 차이를 더 잘 보여준다
*TSNE :
Perplexity = 25, iteration = 500

Result Interpretation - TSNE

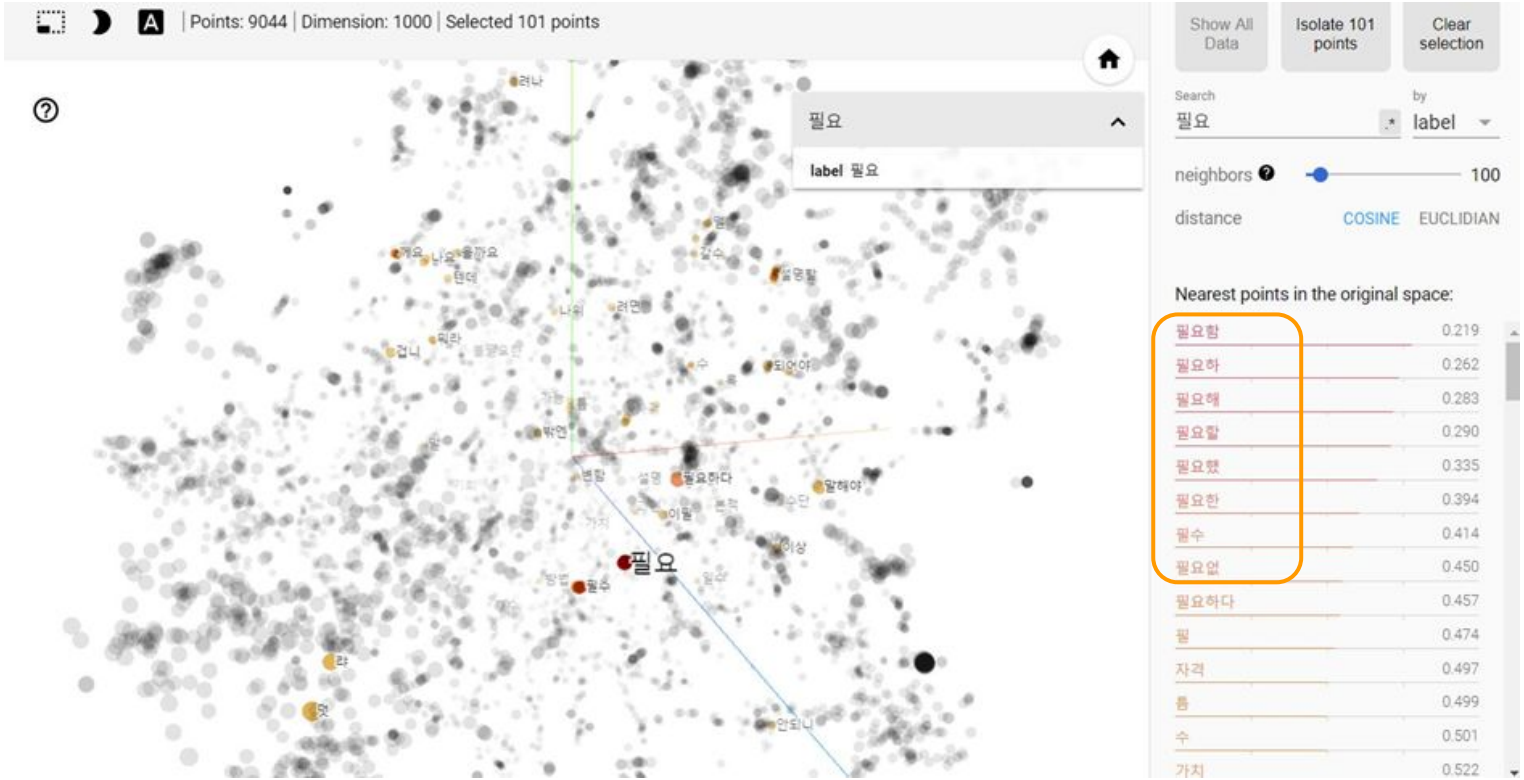


Skipgram - TSNE

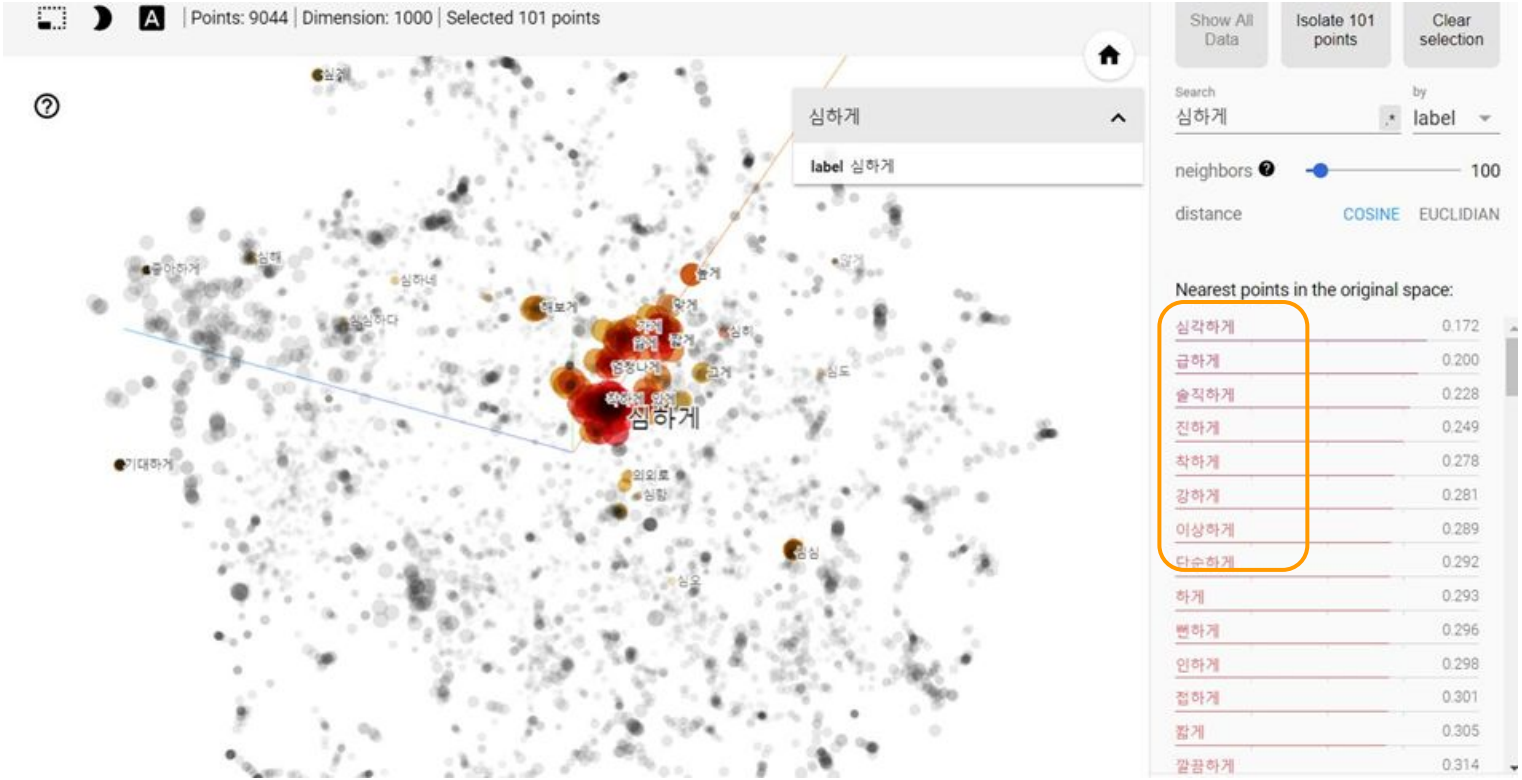


Skipgram - TSNE

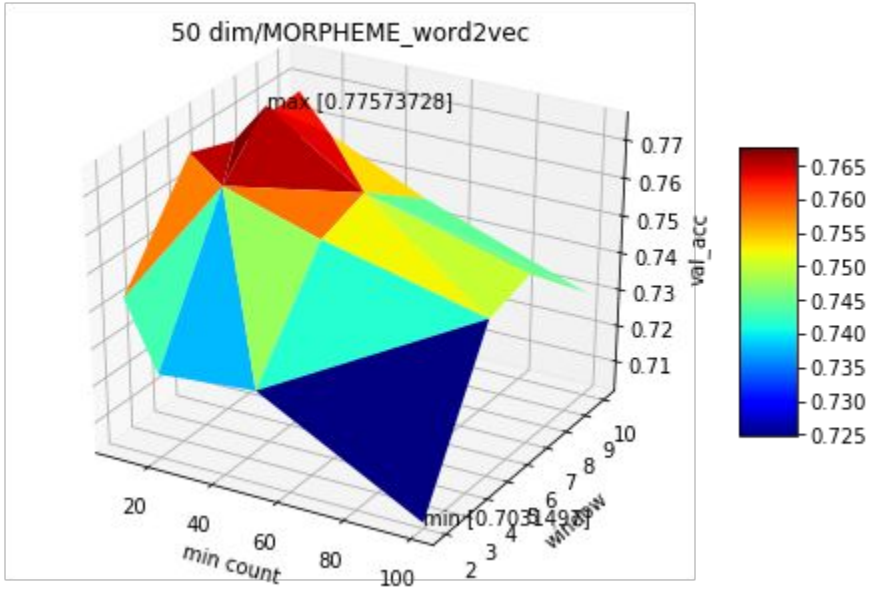
FastText - TSNE

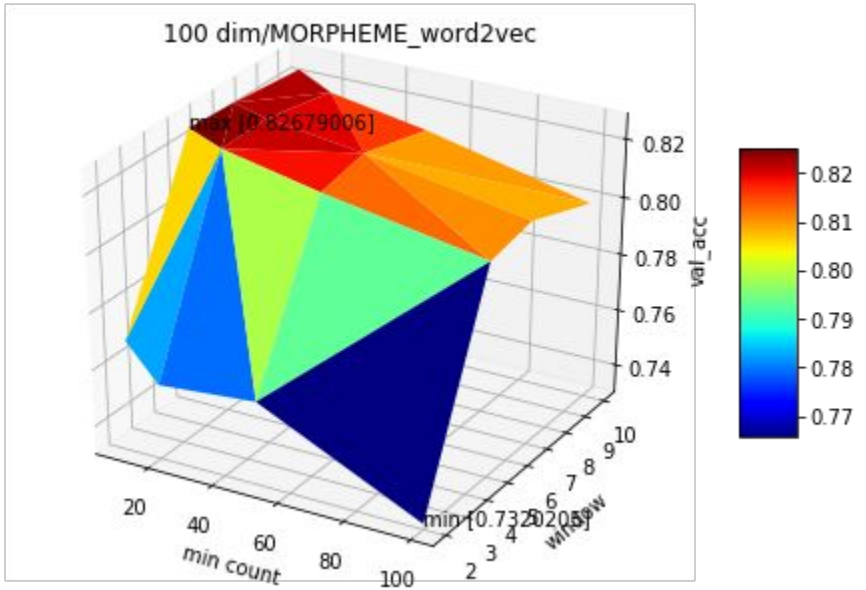


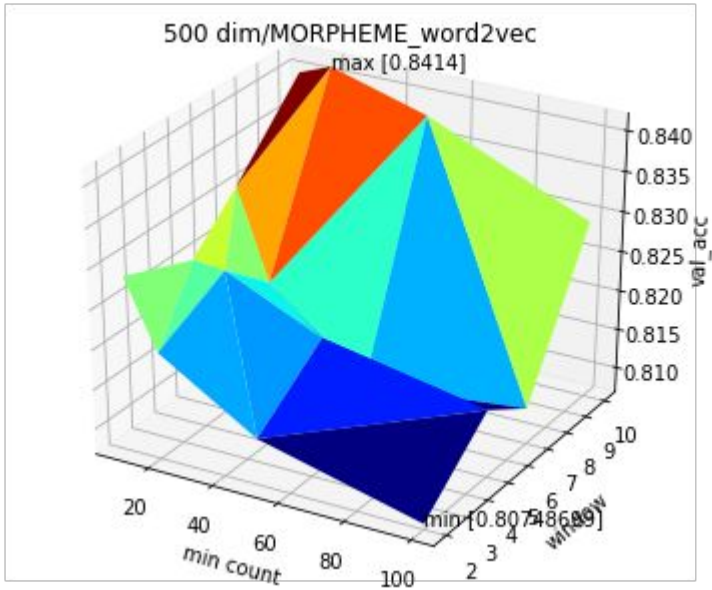
FastText - TSNE

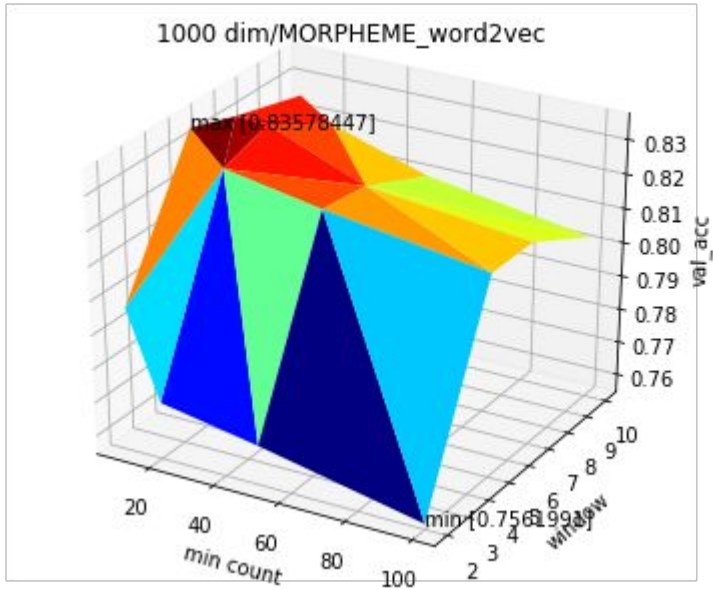


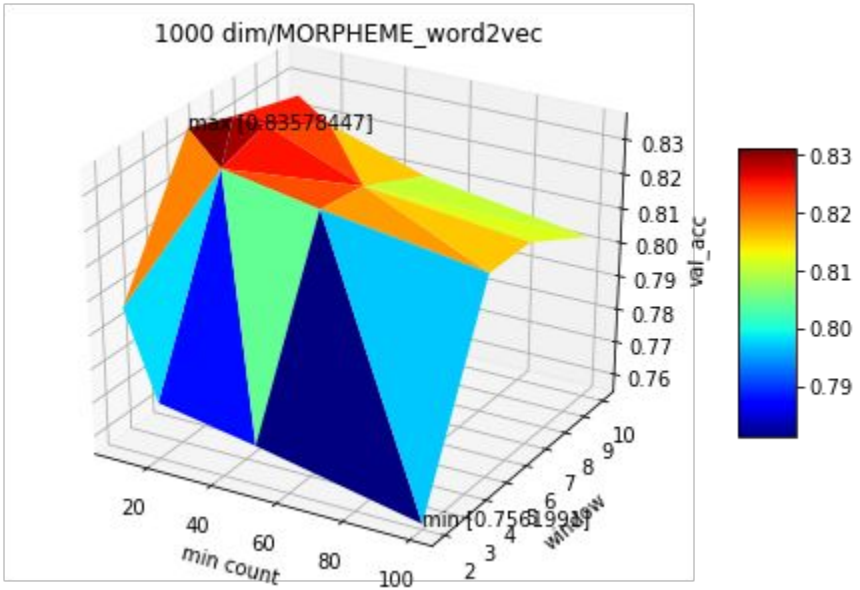
What about Skipgram?






500 dim/MORPHEME_word2vec
max [0.8414]
min [0.80748689]
val_acc
min count
window


1000 dim/MORPHEME_word2vec
max [0.83578447]
min [0.75619994]
val_acc
min count
window



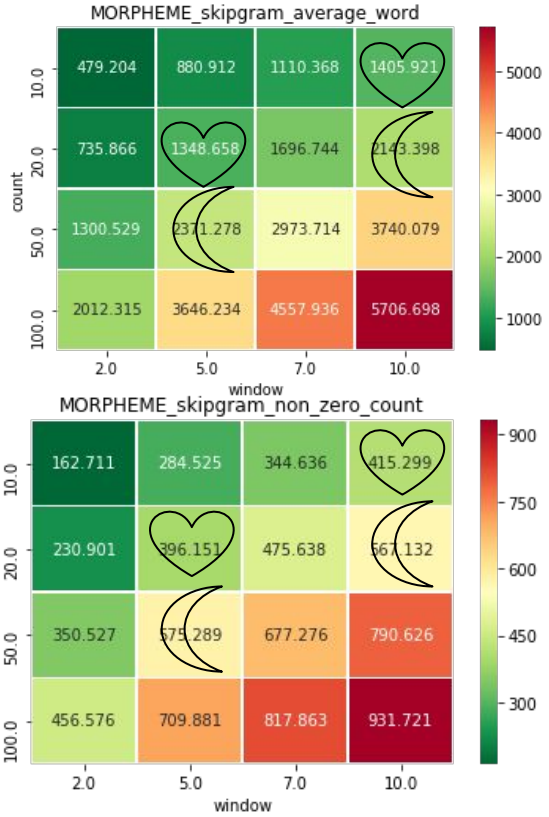
Window

50 : [2 10 5 7]
100 : [2 10 7 5]
300 : [2 10 5 7]
500 : [5 2 7 10]
1000 : [2 10 7 5]

Min Count

50 : [100 50 10 20]
100 : [100 50 20 10]
300 : [50 100 10 20]
500 : [100 50 10 20]
1000 : [100 50 20 10]

Result - Interpretation



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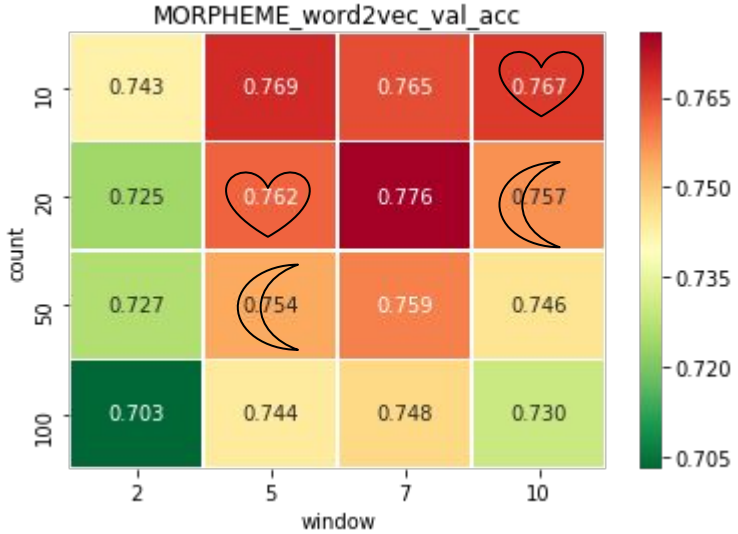
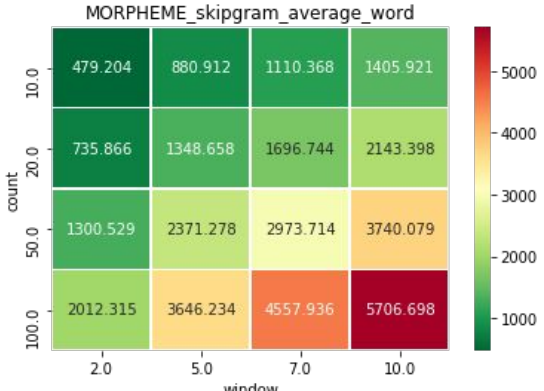
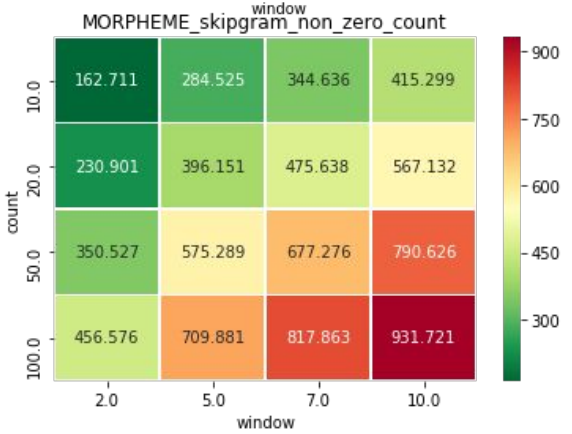


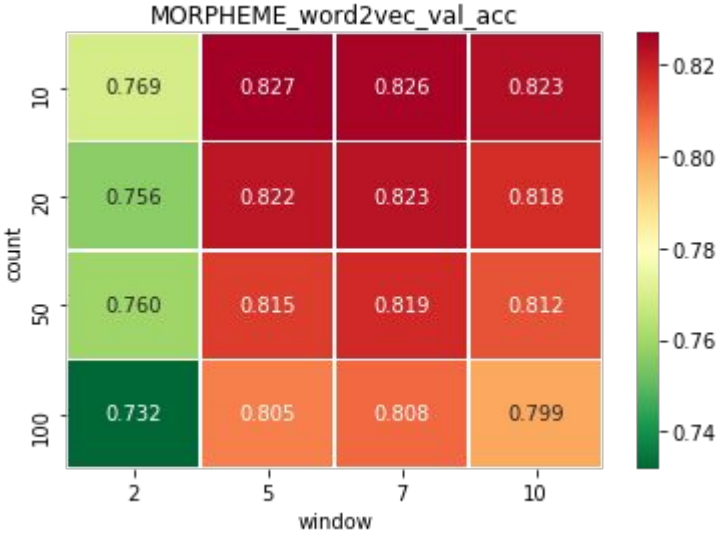
- 차원의 크기와 무관한게 일정한 지점에서 최고점을 형성
- f(average_word, non_zero_count) ≒ val_acc , ∃ f
  - Dimension size 마다 달라짐

Result - Interpretation

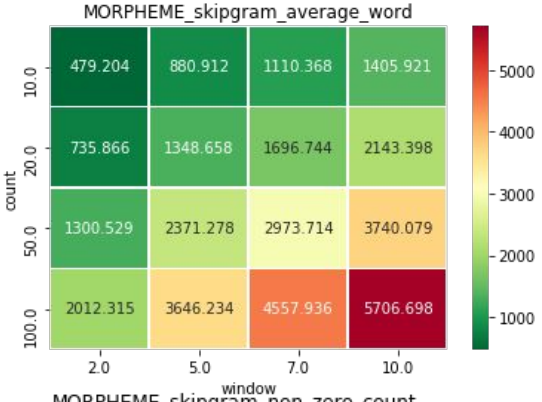


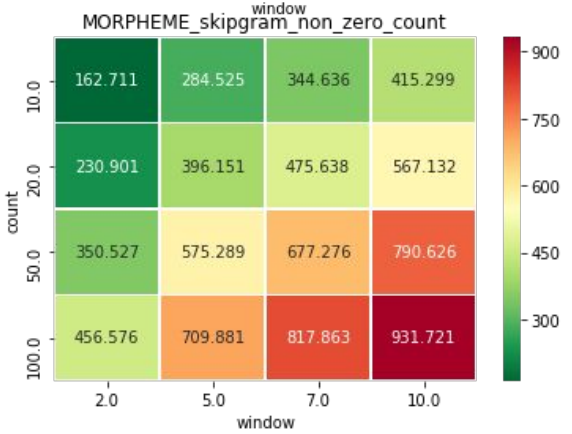


Dim = 100

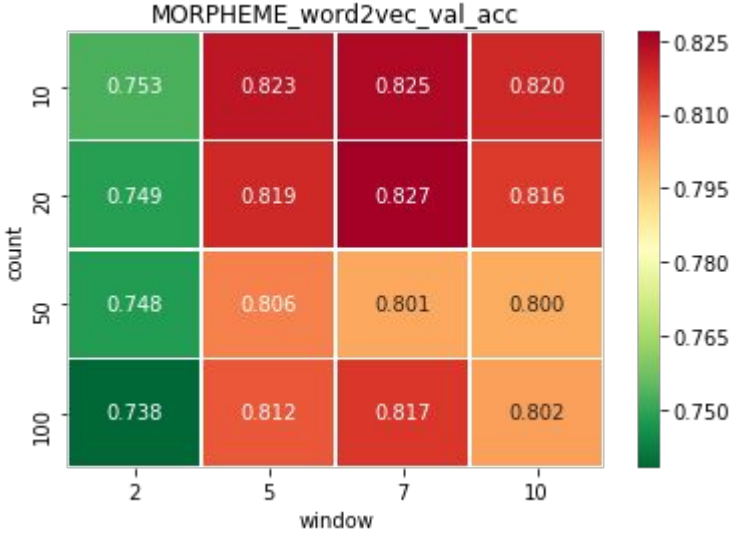


Result - Interpretation

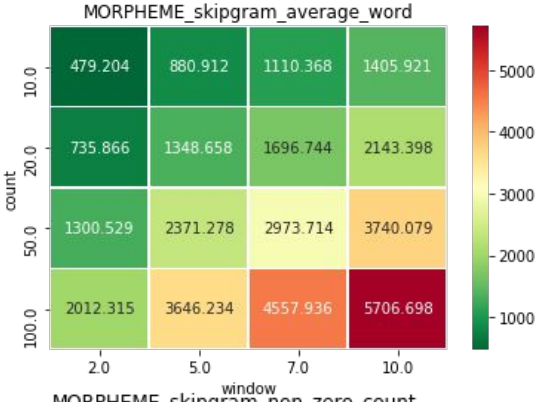


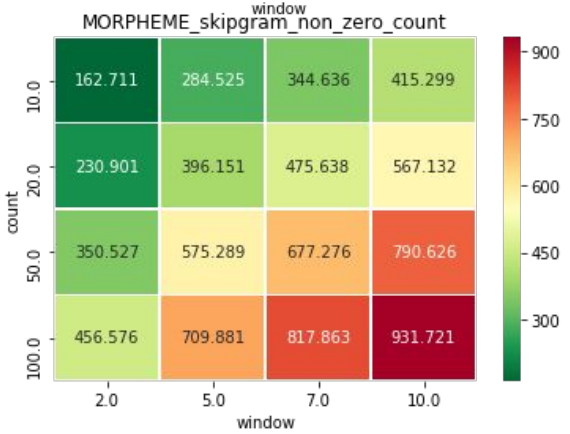


Dim = 300

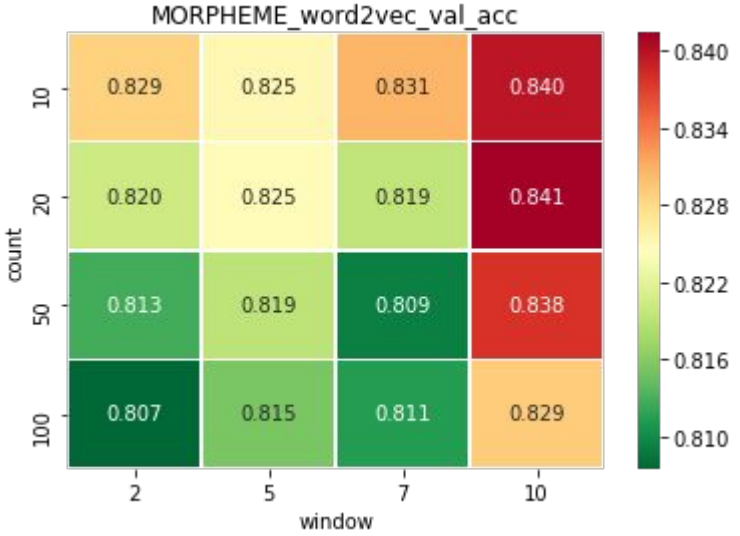


Result - Interpretation

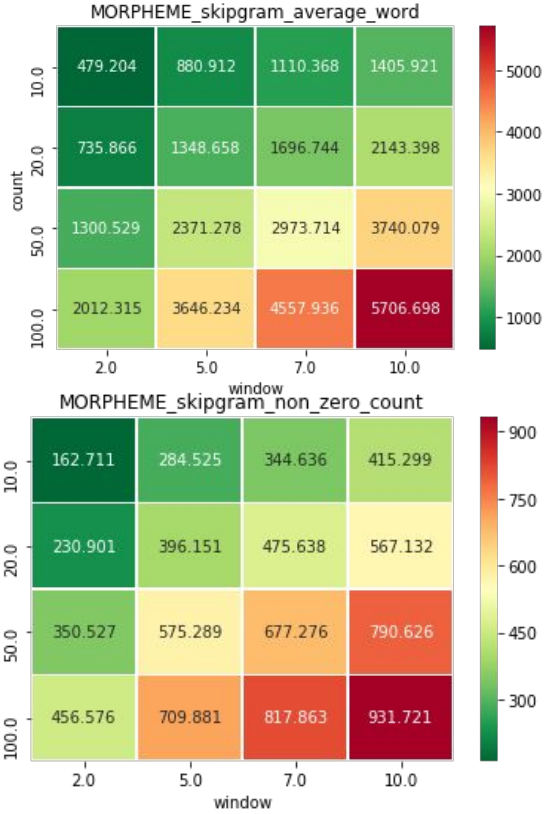




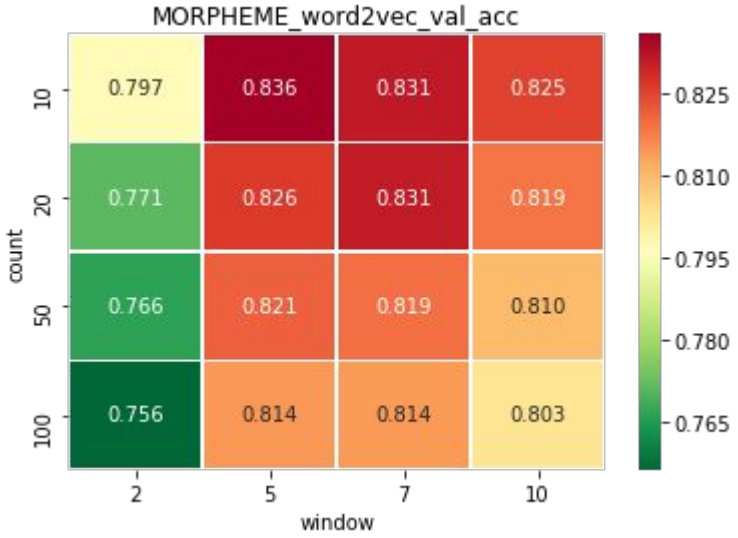
Dim = 500



Result - Interpretation

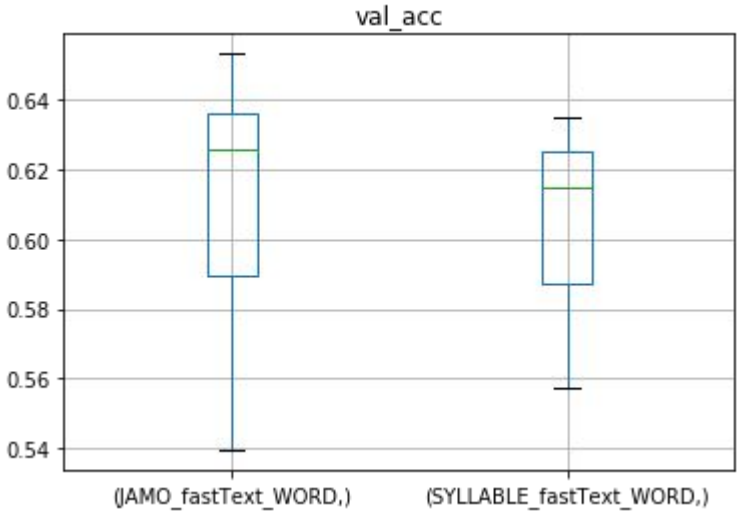


Dim = 1000



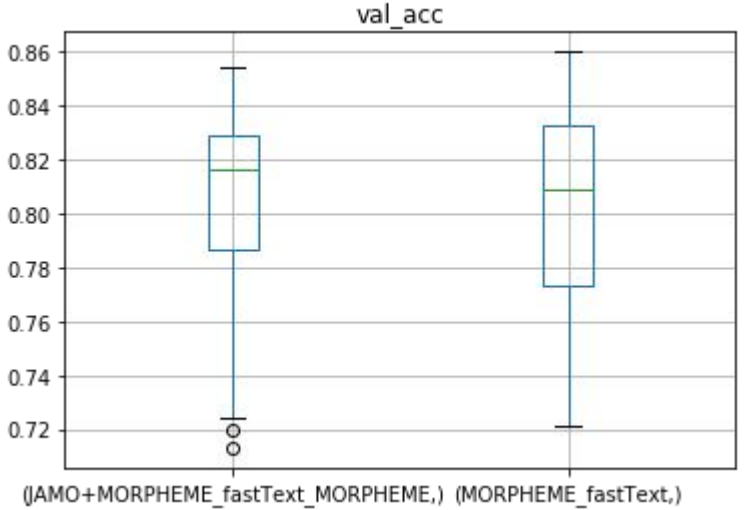
FastText : Grapheme(jamo) vs Syllable

Word



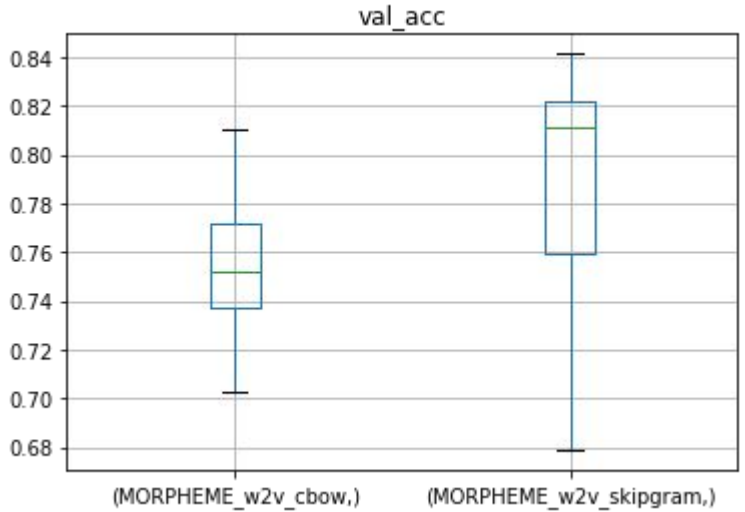
Grapheme > Syllable

Morpheme



Grapheme < Syllable

Word2vec : Skipgram vs Cbow



Word2vec 에서는
SkipGram 이 CBOW보다 더 우세했다.
* 둘 모두 loss함수는 negative sampling 방식이다.

Conclusion

Input Unit

Morpheme 단위의 입력 사용

Parameter

Dimension > Min Count > Window 순으로 최적화

Model

FastText > Skipgram ~ Glove

단, Glove의 경우 어휘당 출현 빈도에 민감

FastText의 경우 자모 단위의 입력이 노이즈로 작용할 수도 있음

Word2vec : Skipgram > Cbow

Reference

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Shi, Tianze, and Zhiyuan Liu. "Linking GloVe with Word2vec." 2014.

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Thank You !, Q&A