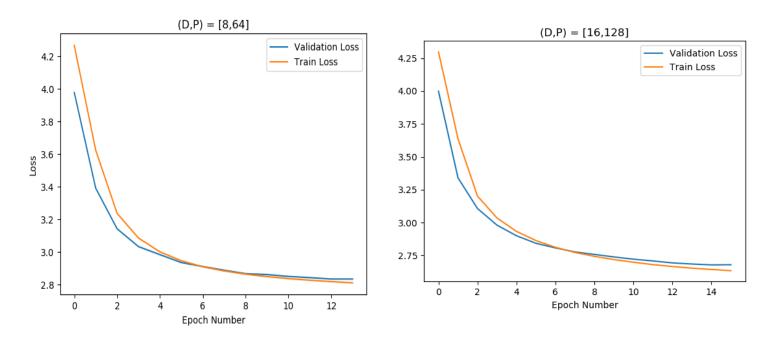
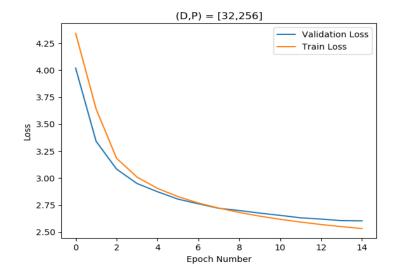
Some Important Notes:

- I implement first question in python that the tester could run code 'python sait_akturk_21501734_hw3.py 1' therefore the tester should get this libraries h5py, matplotlib, sklearn, numpy Install anaconda first then 'conda install matplotlib', 'conda install h5py', 'conda install scikit-learn', 'conda install numpy'.
- I implement second question in matlab therefore the tester should run code in matlab (in python file, you should copy and paste to .m file)environment 'sait_akturk_21501734_hw3.m 2'

QUESTION 1

A) For bigger size of hidden unit help to reduce cross entropy loss and increase accuracy and creates tendency for over-fitting faster, TSNE results become more reasonable results.





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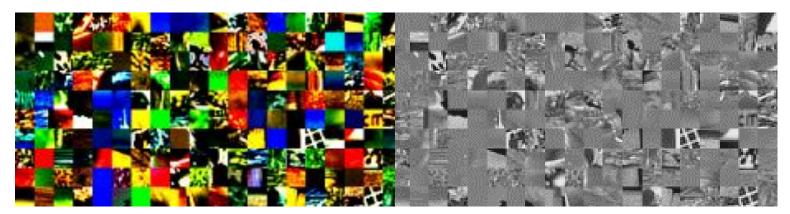
-5

- **B**) Since some words are easy to determine similarity like 'he she it' or 'can could may' we can see that these words that used in similar context are in same clusters and we can identify similar words or words that have similar meanings. Our embedding model find good result, however some specific words like 'john', 'president' used in sentences have no similar words or word that similar meanings. However, embedding does not looking only similarity also find frequency of words used in some trigram structure.
- **C**) I randomly select 5 triagram from test data and get words that 10 maximum probability that I found in test prediction. (1. column is the most likely fourth word, probability drop, when we go to 10. column). I think some triagrams are sensible in the context of fourth word. And I notice that the similar words that we found part b, generally, becomes each other as a prediction because since embedding is also finding similarity between words, the fourth words are generally close the each other in the context of meaning and the place that they are used in sentences.

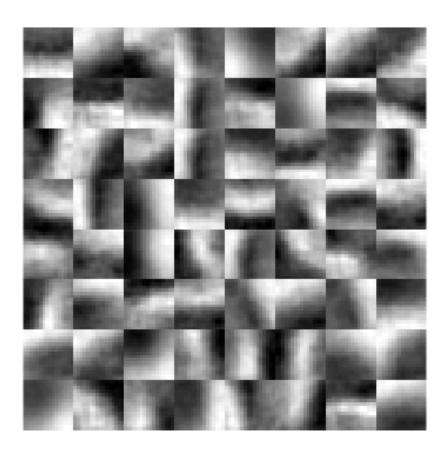
| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---------------|-------|-------|------|-------|------|-------|-------|------|-------|-------|
| think you are | going | | not | here | in | right | there | good | on | out |
| and play my | game | own | day | case | time | life | way | last | best | home |
| work and not | | the | , | for | last | like | at | a | right | have |
| that 's been | the | going | a | there | good | here | like | all | with | right |
| did not like | it | that | this | them | to | the | him | you | me | |

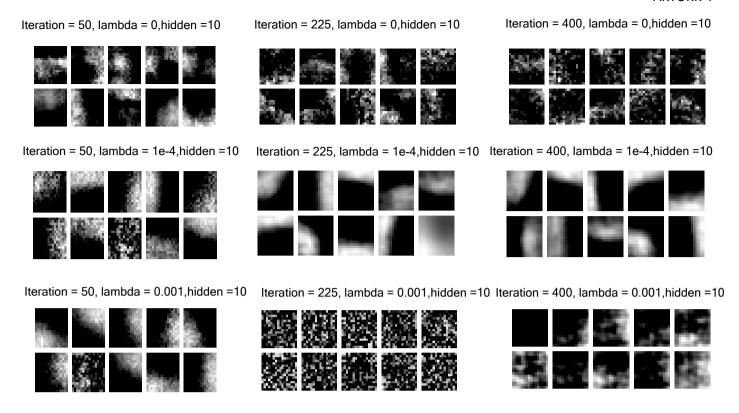
QUESTION 2

A) I randomly select 200 different patches from the data and when I did the normalization I lost color feature therefore as you can see, we could only detect different textures like edge horizontal or diagonal etc. Therefore, I should expect to see in learned features in part b should give this basic features. Since color information is lost the patches that only one color and textures is completely lost due to normalization.

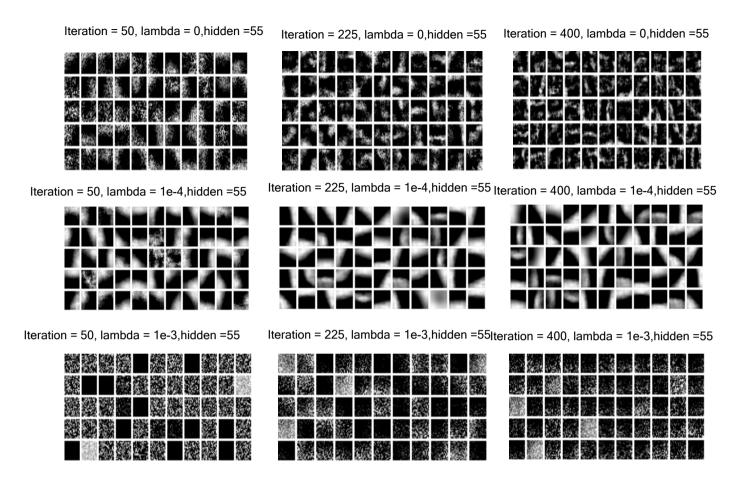


B-C) Our purpose find good features that could represent normalized patches textures, therefore, I experiment with different rho and beta values for code and I found that rho=0.01 and and beta = 2.5 as optimal results. In the beginning I try to reduce final loss that we got from fmincgrad. However, the features that I found became to overfit with data just represent some patches. Therefore, I believe I should find features that could detect basic orientation and illuminance difference like Gabor and first derivate filters. Therefore, I made tradeoff between loss and quality of features. In the end, I got this features that almost represents all oriented gradients inan image(for edge detection for every orientation).

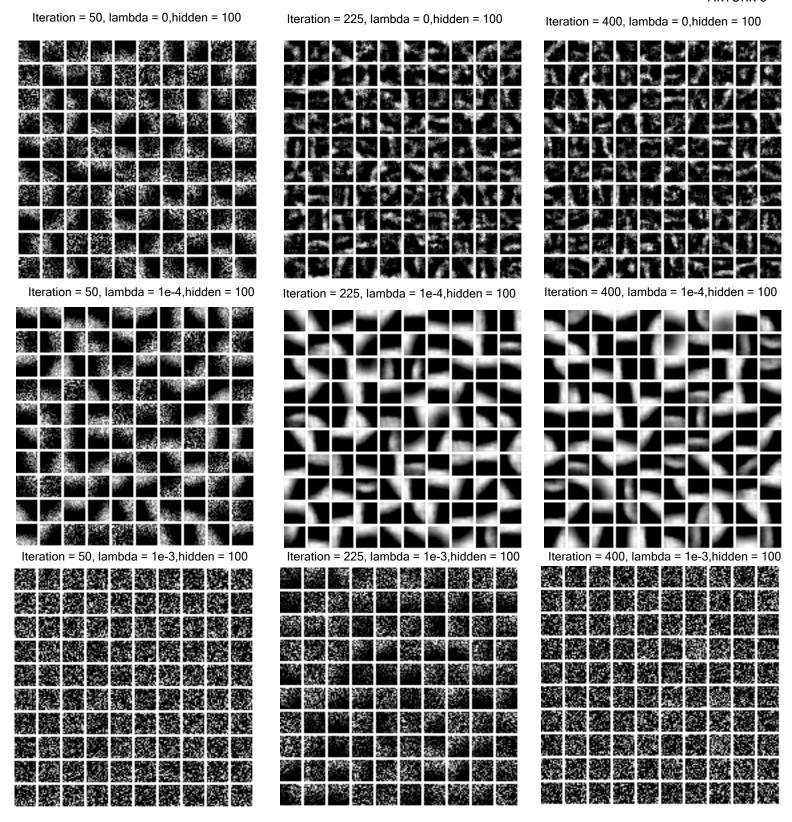




Without Regularization the features from patches have not smooth transition due to overfitting the data. And also we can observe that when we we increase iteration number the features get more and more sharp transitions. And One another thing is that hidden layer number is small and not representative the features for image patches because as we can see the learned features have not all basic oriented gradient that an optimal features should have.



55 hidden units are more representative of basic oriented gradients in image than 10 hidden units. And we can make same observations that the more iterations creates more sharp transition due to memorization of features. And more I2 regularization create more smothed transition of gradients and over regularization creates noise like due to penalty of regularization of learning.



100 hidden units are over representative of patches that some features learned again and again. Same observation could observed here that more iteration makes features transition of gradients sharp and overfit, and more I2 regularization cause to prevent learn anything for bigger lambda not in middle images.