Question 1

1. What range of values for C did you try? Explain, why this range is reasonable. Also explain what search technique you used and why it is appropriate here.
Range: [0.1, 0.15, 0.2, 0.5, 1, 2, 5, 10], because C indicates the inverse of regularization strength, that is, C = 1/λ. Therefore, the loss function with L2-penalty will be $loss = (pred - true)^2 + \frac{1}{C}\sum \theta_i^2$, then C must be a positive float, that's why my range is positive. From the equation we can see smaller C value specify stronger regularization, much penalty to the model's weights which contribute to overfitting. Since these 35000 data may not be fully representative of the real-world data, we don't want overfitting, so a small range of C is my choice.

I used grid search, which trains and tests every combination of parameters to find the best one. And because this task only asks for finding one parameter "C", there are no combinations, therefore using grid search won't take too much time and will be more accurate.

2. What was the best performing C value?
0.1

3. What was your final accuracy?
85.71%

Question 2

PS: the code of my best solution is in "genre_classifier_1.py" about using pretrained transformer, I also hand in the one I tried to build my own model and implement my own token masking preprocessing in "genre_classifier_2.py" since I spent most of time on it.

1. How your final solution works
I use BERT transformer, I tokenize the train_data with the pretrained BERT tokenizer and zeros padding, and then just use the pretrained BERT transformer for sequence classification, because "sentence to genre" is just sequence classification. Furthermore, answered in sub question 4.

2. How you trained and tested your model (e.g. validation split(s), hyperparameter search ...)
The training set is too small compares to the test set, moreover the test set labels are uneven without lots of label-1(science fiction), so I decide not using validation split for any early-stopping or learning_rate_decreasing purpose, though I already tried few times with almost futile efforts. Therefore, I prefer to not waste any training data, use the whole training set to

train the model. Since I use pre-trained transformer from the library transformers, so I do not have too much hyperparameter to test, I only try to set the batch_size to 32 (relatedly ok compared to the size of the small training set) because the default batch_size is 8. I do so because I want the gradient descent to happen in the better direction smoothly.

3.What models you tested, which worked, and which didn't
I knew that transformer might be the best model for the purpose of this task, however I still try to build many models myself, one of them is a model of concatenation of MLP and Bi-LSTM. It uses TF-IDF vector input for MLP and embedding input for LSTM, then use these two outputs as input to the final MLP. I also mask the training set in case of predicting unknown tokens. So my training set contain the original one and the masked one. The result I got without anything pretrained is not that high, mostly around 0.59~0.6.
Using normal RNN model without pretrained embedding or using only TF-IDF method doesn't work well, mostly get score below 0.5.
I stop trying anything outside transformer due to it cost lot of time on training, then I start using transformer with pretrained materials.

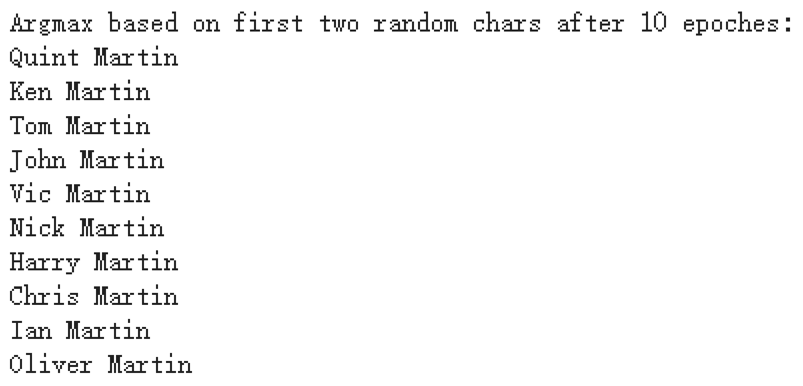
4.Why you think these other models didn't work
For example, TF-IDF. The vocabulary is large, which results in each vectors has lots of zeros. Because there are only less than 5% of vocabulary appear in each document. As a high dimension input to ML model, it is not good to have so many empty features, it will decrease the performance of the model.
Models with RNN cannot beat transformers in this task, I think its because RNN training is serial, that is, the current word has to be passed into the RNN cell before the later words being passed to RNN cell. And RNN has problem about relations between tokens, for example in this sentence "I am a computer science student", relationship between "I" and "am" is very close, but between "I" and "student" is relatively far. Transformer uses Attention mechanism, the training is parallel, that is, all words are trained at the same time, so it will not have the problem about long sentence as RNN has, and it has also increase calculation efficiency. Because parallel training ignores the order relationship between the tokens, transformer also uses positional encoding to understand the order of the tokens. Transformer use the combination of QKV(query, key, value) instead of normal embedding, it bring the words from the spatial space to another much efficient space.

Question 3

```
Epoch: [1/10], loss: 2.8788, val_loss: 2.9343.
Epoch: [2/10], loss: 2.6151, val_loss: 2.6948.
Epoch: [3/10], loss: 2.4799, val_loss: 2.5827.
Epoch: [4/10], loss: 2.3996, val_loss: 2.5244.
Epoch: [5/10], loss: 2.3469, val_loss: 2.4894.
Epoch: [6/10], loss: 2.3155, val_loss: 2.4660.
```

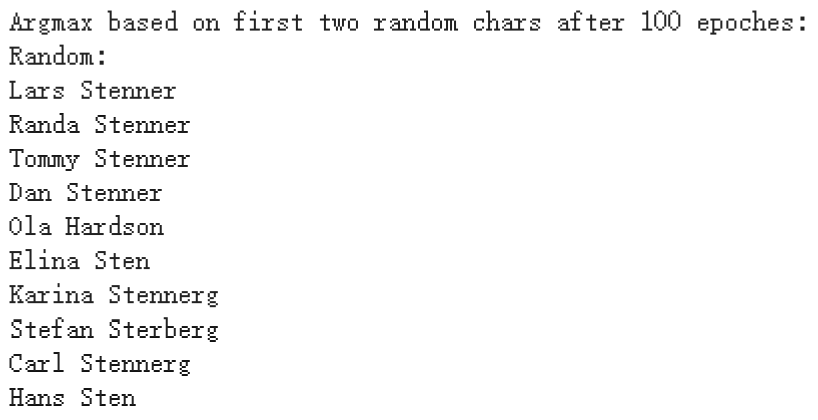
Epoch: [7/10], loss: 2.2909, val_loss: 2.4471.
Epoch: [8/10], loss: 2.2707, val_loss: 2.4327.
Epoch: [9/10], loss: 2.2521, val_loss: 2.4203.
Epoch: [10/10], loss: 2.2350, val_loss: 2.4088.
Argmax: Jon Brich
Random:
Adars Maskelnom
Bocex Burle
Rilices Crannun
Bran Alics
Delk We Dobgino
Conthuiy Mecborid
Ere Rims
Asrard Horrgt
Macet McAgich
Deran Cuwehn

My additional discover is that, the GRU hidden layer size is very important for the linear separability of the RNNLM. Because the vocabulary size is 66, 1 layer GRU hidden layer size is better be much higher than vocabulary size, or it will be hard to get good performance or slow to converge for the RNNLM.
For example, as shown in below result, the model learns that a 'space' has meaningful meaning, however, its performance after such a token is so bad,



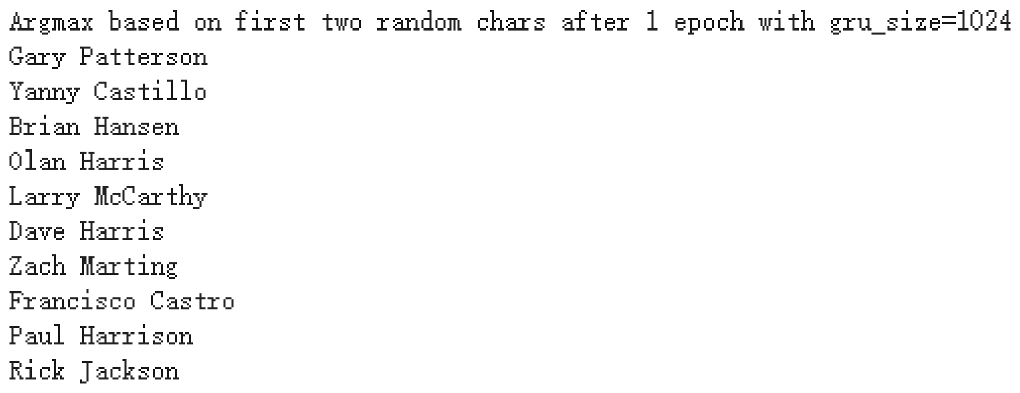
```
Argmax based on first two random chars after 10 epoches:
Quint Martin
Ken Martin
Tom Martin
John Martin
Vic Martin
Nick Martin
Harry Martin
Chris Martin
Ian Martin
Oliver Martin
```

And if I keep training after 100 epoches, I get below result, "Stenner, Sten, Stennerg, Sterberg" shows that the linear separability is starting to be better. This dataset is a bit large to train, using a small training dataset to train 1000+ epoches shows that it will eventually be random on the names after first 'space'.



```
Argmax based on first two random chars after 100 epoches:
Random:
Lars Stenner
Randa Stenner
Tommy Stenner
Dan Stenner
Ola Hardson
Elina Sten
Karina Stennerg
Stefan Sterberg
Carl Stennerg
Hans Sten
```

Result for GRU hidden layer size = 1024



```
Argmax based on first two random chars after 1 epoch with gru_size=1024
Gary Patterson
Yanny Castillo
Brian Hansen
Olan Harris
Larry McCarthy
Dave Harris
Zach Marting
Francisco Castro
Paul Harrison
Rick Jackson
```