In [22]:
```
!ln -sf /opt/bin/nvidia-smi /usr/bin/nvidia-smi
!pip install gputil
!pip install psutil
!pip install humanize
import psutil
import humanize
import os
import GPUtil as GPU
GPUs = GPU.getGPUs()
# XXX: only one GPU on Colab and isn’t guaranteed
gpu = GPUs[0]
def printm():
 process = psutil.Process(os.getpid())
 print("Gen RAM Free: " + humanize.naturalsize( psutil.virtual_memory().available ), " | Proc size: "
+ humanize.naturalsize( process.memory_info().rss))
 print("GPU RAM Free: {0:.0f}MB | Used: {1:.0f}MB | Util {2:3.0f}% | Total {3:.0f}MB".format(gpu.memo
ryFree, gpu.memoryUsed, gpu.memoryUtil*100, gpu.memoryTotal))
printm()
```

```
Requirement already satisfied: gputil in /usr/local/lib/python3.6/dist-packages (1.4.0)
Requirement already satisfied: psutil in /usr/local/lib/python3.6/dist-packages (5.4.8)
Requirement already satisfied: humanize in /usr/local/lib/python3.6/dist-packages (0.5.1)
Gen RAM Free: 12.5 GB  | Proc size: 502.1 MB
GPU RAM Free: 11441MB | Used: 0MB | Util   0% | Total 11441MB
```

In [23]:
```
# importing necessary libraries
import re
import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
import numpy as np
import pandas as pd
import random as rn
import seaborn as sns
import tensorflow as tf
from tqdm.notebook import tqdm
import matplotlib.pyplot as plt
from urllib.parse import urlparse
from tensorflow.keras.models import Model
from tensorflow.keras import backend as K
from tensorflow.keras import regularizers
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from tensorflow.compat.v1.keras.layers import CuDNNGRU
from tensorflow.keras.preprocessing.text import Tokenizer
from sklearn.feature_extraction.text import TfidfVectorizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.layers import concatenate, GRU, Input, Embedding, Dense, Flatten, Dropout, Batc
hNormalization, GlobalAveragePooling1D
```

In [24]:
```
import warnings
K.set_floatx('float64')
warnings.filterwarnings('ignore')
```

In [25]:
```
np.random.seed(12)
tf.random.set_seed(13)
rn.seed(14)
```

In [26]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/
drive", force_remount=True).
```

In [27]:
```
#clean data
puncts = [',', '.', '"', ':', ')', '(', '-', '!', '?', '|', ';', '$', '&', '/', '[', ']', '>', '%',
'=', '#', '*', '+', '\\', '•',  '~', '@', '£',
 '·', '_', '{', '}', '©', '^', '®', '`',  '<', '→', '°', '€', '™', '›',  '♥', '←', '×', '§', '″', '′'
, 'Â', '█', '½', 'à', '…', '\xa0', '\t',
 '“', '★', '”', '–', '●', 'â', '►', '−', '¢', '²', '¬', '░', '¶', '↑', '±', '¿', '▾', '═', '¦', '║',
'―', '¥', '▓', '—', '‹', '─', '\u3000', '\u202f',
 '▒', '：', '¼', '⊕', '▼', '▪', '†', '■', '’', '▀', '¨', '▄', '♫', '☆', 'é', '¯', '♦', '¤', '▲', 'è',
'¸', '¾', 'Ã', '⋅', '‘', '∞', '«',
 '∙', '）', '↓', '、', '│', '（', '»', '，', '♪', '╩', '╚', '³', '・', '╦', '╣', '╔', '╗', '▬', '❤',
'ï', 'Ø', '¹', '≤', '‡', '√', ]

mispell_dict = {"aren't" : "are not", "can't" : "cannot", "couldn't" : "could not", "couldnt" : "coul
d not", "didn't" : "did not", "doesn't" : "does not",
                "doesnt" : "does not", "don't" : "do not", "hadn't" : "had not", "hasn't" : "has not"
, "haven't" : "have not", "havent" : "have not",
                "he'd" : "he would", "he'll" : "he will", "he's" : "he is", "i'd" : "I would", "i'd"
: "I had", "i'll" : "I will", "i'm" : "I am",
                "isn't" : "is not","it's" : "it is","it'll":"it will", "i've" : "I have", "let's" :
"let us", "mightn't" : "might not", "mustn't" : "must not",
                "shan't" : "shall not", "she'd" : "she would", "she'll" : "she will", "she's" : "she
 is", "shouldn't" : "should not", "shouldnt" : "should not",
                "that's" : "that is", "thats" : "that is", "there's" : "there is", "theres" : "there
 is", "they'd" : "they would", "they'll" : "they will",
                "they're" : "they are", "theyre":  "they are", "they've" : "they have", "we'd" : "we
 would", "we're" : "we are", "weren't" : "were not",
                "we've" : "we have", "what'll" : "what will", "what're" : "what are", "what's" : "wha
t is", "what've" : "what have", "where's" : "where is",
                "who'd" : "who would", "who'll" : "who will", "who're" : "who are", "who's" : "who i
s", "who've" : "who have", "won't" : "will not",
                "wouldn't" : "would not", "you'd" : "you would", "you'll" : "you will", "you're" : "y
ou are", "you've" : "you have", "'re": " are",
                "wasn't": "was not", "we'll":" will", "didn't": "did not", "tryin'":"trying"}

def clean_text(x):
    x = str(x).replace("\n","")
    for punct in puncts:
        x = x.replace(punct, f' {punct} ')
    return x

def clean_numbers(x):
    x = re.sub('[0-9]{5,}', '#####', x)
```

```
    x = re.sub('[0-9]{4}', '####', x)
    x = re.sub('[0-9]{3}', '###', x)
    x = re.sub('[0-9]{2}', '##', x)
    return x

def _get_mispell(mispell_dict):
    mispell_re = re.compile('(%s)' % '|'.join(mispell_dict.keys()))
    return mispell_dict, mispell_re

def replace_typical_misspell(text):
    mispellings, mispellings_re = _get_mispell(mispell_dict)

    def replace(match):
        return mispellings[match.group(0)]

    return mispellings_re.sub(replace, text)

def clean_data(df, columns):
    for col in tqdm(columns):
        df[col] = df[col].apply(lambda x: re.sub(' +', ' ', x)).values
        df[col] = df[col].apply(lambda x: re.sub('\n', '', x)).values
        df[col] = df[col].apply(lambda x: clean_numbers(x)).values
        df[col] = df[col].apply(lambda x: replace_typical_misspell(x)).values
        df[col] = df[col].apply(lambda x: clean_text(x.lower())).values
        df[col] = df[col].apply(lambda x: x.lower()).values
        df[col] = df[col].apply(lambda x: re.sub(' +', ' ', x)).values

    return df
```

In [28]:
```
def fix_upvotes(x):
  try:
    return int(x.split('.')[0])
  except:
    return 0
```

In [29]:
```
from sklearn.preprocessing import MinMaxScaler
def preprocess_data(train, test, new_features_train, new_features_test, flag=0):

  y = train[train.columns[11:]] # storing the target labels in 'y'

  # I'll be cleaning and adding the domain name from the website's url.
  find = re.compile(r"^[^.]*")
  train['clean_url'] = train['url'].apply(lambda x: re.findall(find, urlparse(x).netloc)[0])
  test['clean_url'] = test['url'].apply(lambda x: re.findall(find, urlparse(x).netloc)[0])

  # creating train and test data
  X = train[['question_title', 'question_body', 'answer', 'clean_url', 'category']]
  X = pd.concat([X, new_features_train], axis=1)
  X_test = test[['question_title', 'question_body', 'answer', 'clean_url', 'category']]
  X_test = pd.concat([X_test, new_features_test], axis=1)
  text_features = ['question_title', 'question_body', 'answer', 'comments_0', 'answer_1',
                   'comment_1', 'answer_2','comment_2', 'answer_3', 'comment_3']
  num_features = ['upvotes', 'reputation_q', 'gold_q', 'silver_q', 'bronze_q',
                  'reputation_a', 'gold_a', 'silver_a', 'bronze_a']

  # Cleaning data for contracted words, numbers and punctuations.
  X = clean_data(X, text_features)
  X_test = clean_data(X_test, text_features)

  # splitting the data into train and cv sets.
  X_train, X_cv, y_train, y_cv = train_test_split(X, y, test_size=0.1, random_state=42)

  if flag==1:
    return X_train, X_cv, y_train.values, y_cv.values

  # I'll be using these features as categorical OHE features.
  features = ['clean_url', 'category']
  # creating categorical features for train, cv and test data.
  ohe = OneHotEncoder()
  ohe.fit(X_train[features])
  categorical_features_train = ohe.transform(X_train[features]).todense()
  categorical_features_cv = ohe.transform(X_cv[features]).todense()
  categorical_features_test = ohe.transform(X_test[features]).todense()


  # I'll also be using the following scraped numerical features.
  min_max_scaler = MinMaxScaler()
```

```
    num_features = ['upvotes', 'reputation_q', 'gold_q', 'silver_q', 'bronze_q',
                    'reputation_a', 'gold_a', 'silver_a', 'bronze_a']
    numerical_features_train = min_max_scaler.fit_transform(X_train[num_features].values)
    numerical_features_cv = min_max_scaler.transform(X_cv[num_features].values)
    numerical_features_test = min_max_scaler.transform(X_test[num_features].values)

    print('created categorical features, now loading glove vocab...')

    # I'm henerating a dictionary 'embeddings_index' that holds all the words in the glove.6b as keys a
nd their 300 dimensional embeddings as values.
    embeddings_index = dict()
    oov_vector = np.zeros(300)
    f = open('glove.6B.300d.txt')
    for line in tqdm(f):
      values = line.split()
      word = values[0]
      coefs = np.asarray(values[1:], dtype='float32')
      embeddings_index[word] = coefs
      oov_vector += coefs
    f.close()
    print('Loaded %s word vectors.' % len(embeddings_index))
    print('tokenizing the sentences of input data..')

    oov_vector = oov_vector/len(embeddings_index)

############################################################
    # generating tokens for 'question_title'
    tokenizer = Tokenizer(num_words=None, filters='', lower=True, split=' ', char_level=False, oov_toke
n='oov_word', document_count=0)
    tokenizer.fit_on_texts(X_train['question_title'].values)

    train_title = tokenizer.texts_to_sequences(X_train['question_title'].values)
    cv_title = tokenizer.texts_to_sequences(X_cv['question_title'].values)
    test_title = tokenizer.texts_to_sequences(X_test['question_title'].values)

    # padding the 'question_title' sequences and truncating the sentences of length is > max_length def
ined above.
    train_title = pad_sequences(train_title, maxlen=max_length_title, padding='post', value=0)
    cv_title = pad_sequences(cv_title, maxlen=max_length_title, padding='post', value=0)
    test_title = pad_sequences(test_title, maxlen=max_length_title, padding='post', value=0)

    # creating embedding_matrix that holds the words in 'question_title' as keys and their respective 3
00d embeddings as values.
```

```
  # I'll use this embedding_matrix in the embedding layer of my model.
  title_vocab_size = len(tokenizer.word_index) + 1
  embedding_matrix_title = np.zeros((title_vocab_size, 300))
  for word, i in tqdm(tokenizer.word_index.items()):
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
      embedding_matrix_title[i] = embedding_vector
    else:
      embedding_matrix_title[i] = oov_vector
  print('created embedding matrix for question_title...')

#############
  # generating tokens for 'question_body'
  tokenizer = Tokenizer(num_words=None, filters='', lower=True, split=' ', char_level=False, oov_toke
n='oov_word', document_count=0)
  tokenizer.fit_on_texts(X_train['question_body'].values)

  train_body = tokenizer.texts_to_sequences(X_train['question_body'].values)
  cv_body = tokenizer.texts_to_sequences(X_cv['question_body'].values)
  test_body = tokenizer.texts_to_sequences(X_test['question_body'].values)

  # padding the 'question_body' sequences and truncating the sentences of length is > max_length defi
ned above.
  train_body = pad_sequences(train_body, maxlen=max_length_body, padding='post', value=0)
  cv_body = pad_sequences(cv_body, maxlen=max_length_body, padding='post', value=0)
  test_body = pad_sequences(test_body, maxlen=max_length_body, padding='post', value=0)

  # creating embedding_matrix that holds the words in 'question_body' as keys and their respective 30
0d embeddings as values.
  # I'll use this embedding_matrix in the embedding layer of my model.
  body_vocab_size = len(tokenizer.word_index) + 1
  embedding_matrix_body = np.zeros((body_vocab_size, 300))
  for word, i in tqdm(tokenizer.word_index.items()):
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
      embedding_matrix_body[i] = embedding_vector
    else:
      embedding_matrix_body[i] = oov_vector
  print('created embedding matrix for question_body...')

##############
  # generating tokens for 'answer + comments_0'
  tokenizer = Tokenizer(num_words=None, filters='', lower=True, split=' ', char_level=False, oov_toke
```

```
n='oov_word', document_count=0)
  tokenizer.fit_on_texts(X_train['answer'].values)

  train_answer = tokenizer.texts_to_sequences(X_train['answer'].values)
  cv_answer = tokenizer.texts_to_sequences(X_cv['answer'].values)
  test_answer = tokenizer.texts_to_sequences(X_test['answer'].values)

  # padding the 'answer' sequences and truncating the sentences of length is > max_length defined abo
ve.
  train_answer = pad_sequences(train_answer, maxlen=max_length_answer, padding='post', value=0)
  cv_answer = pad_sequences(cv_answer, maxlen=max_length_answer, padding='post', value=0)
  test_answer = pad_sequences(test_answer, maxlen=max_length_answer, padding='post', value=0)

  # creating embedding_matrix that holds the words in 'answer' as keys and their respective 300d embe
ddings as values.
  # I'll use this embedding_matrix in the embedding layer of my model.
  answer_vocab_size = len(tokenizer.word_index) + 1
  embedding_matrix_answer = np.zeros((answer_vocab_size, 300))
  for word, i in tqdm(tokenizer.word_index.items()):
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
      embedding_matrix_answer[i] = embedding_vector
    else:
      embedding_matrix_answer[i] = oov_vector
  print('created embedding matrix for answer...')

#####################################################################

 # generating tokens for 'answer_1 + comments_1 + answer_2 + comments_2 + answer_3 + comments_3'
  tokenizer = Tokenizer(num_words=None, filters='', lower=True, split=' ', char_level=False, oov_toke
n='oov_word', document_count=0)
  tokenizer.fit_on_texts((X_train['comments_0'] +' '+ X_train['answer_1'] +' '+ X_train['comment_1']
+ ' '+\
                          X_train['answer_2'] +' '+ X_train['comment_2'] + ' '+ X_train['answer_3'] +
' '+\
                          X_train['comment_3']).values)

  train_scraped = tokenizer.texts_to_sequences((X_train['comments_0'] +' '+ X_train['answer_1'] +' '+
X_train['comment_1'] + ' '+\
                          X_train['answer_2'] +' '+ X_train['comment_2'] + ' '+ X_train['answer_3'] +
' '+\
                          X_train['comment_3']).values)
```

```
  cv_scraped = tokenizer.texts_to_sequences((X_cv['comments_0'] +' '+ X_cv['answer_1'] +' '+ X_cv['co
mment_1'] + ' '+\
                          X_cv['answer_2'] +' '+ X_cv['comment_2'] + ' '+ X_cv['answer_3'] +' '+\
                          X_cv['comment_3']).values)

  test_scraped = tokenizer.texts_to_sequences((X_test['comments_0'] +' '+ X_test['answer_1'] +' '+ X_
test['comment_1'] + ' '+\
                          X_test['answer_2'] +' '+ X_test['comment_2'] + ' '+ X_test['answer_3'] +' '
+\
                          X_test['comment_3']).values)

  # padding the 'answer' sequences and truncating the sentences of length is > max_length defined abo
ve.
  train_scraped = pad_sequences(train_scraped, maxlen=max_length_scraped, padding='post', value=0)
  cv_scraped = pad_sequences(cv_scraped, maxlen=max_length_scraped, padding='post', value=0)
  test_scraped = pad_sequences(test_scraped, maxlen=max_length_scraped, padding='post', value=0)

  # creating embedding_matrix that holds the words in 'answer' as keys and their respective 300d embe
ddings as values.
  # I'll use this embedding_matrix in the embedding layer of my model.
  scraped_vocab_size = len(tokenizer.word_index) + 1
  embedding_matrix_scraped = np.zeros((scraped_vocab_size, 300))
  for word, i in tqdm(tokenizer.word_index.items()):
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
      embedding_matrix_scraped[i] = embedding_vector
    else:
      embedding_matrix_scraped[i] = oov_vector
  print('created embedding matrix for answer...')

################################################################################

  # Preparing data for tfidf features by concatenating 'question_title', 'question_body', 'answer' an
d scraped features.
  text_train = []
  text_cv = []
  text_test = []
  for row in X_train[text_features].values:
    text_train.append(' '.join(row))
  for row in X_cv[text_features].values:
    text_cv.append(' '.join(row))
  for row in X_test[text_features].values:
    text_test.append(' '.join(row))
```

```
  print('prepared data for tfidf now generating tfidf features...')

  tfidf = TfidfVectorizer(ngram_range=(2,5), max_features=max_features_tfidf)
  train_tfidf = tfidf.fit_transform(text_train)
  cv_tfidf = tfidf.transform(text_cv)
  test_tfidf = tfidf.transform(text_test)
  print('data preprocessing completed!')

  return train_title, train_body, train_answer, train_scraped, categorical_features_train, train_tfid
f.toarray(), cv_title, cv_body, cv_answer, cv_scraped, categorical_features_cv, cv_tfidf.toarray(), t
est_title, test_body, test_answer, test_scraped, categorical_features_test, test_tfidf.toarray(), y_t
rain.values, y_cv.values, title_vocab_size, body_vocab_size, answer_vocab_size, scraped_vocab_size, e
mbedding_matrix_title, embedding_matrix_body, embedding_matrix_answer, embedding_matrix_scraped, nume
rical_features_train, numerical_features_cv, numerical_features_test
```

In [30]:

```
def collect_data_for_model(train, test, new_features_train, new_features_test):
  train_title, train_body, train_answer, train_scraped, categorical_features_train, train_tfidf, cv_t
itle, cv_body, cv_answer, cv_scraped, categorical_features_cv, cv_tfidf, test_title, test_body, test_
answer, test_scraped, categorical_features_test, test_tfidf, y_train, y_cv, title_vocab_size, body_vo
cab_size, answer_vocab_size, scraped_vocab_size, embedding_matrix_title, embedding_matrix_body, embed
ding_matrix_answer, embedding_matrix_scraped, numerical_features_train, numerical_features_cv, numeri
cal_features_test = preprocess_data(train, test, new_features_train, new_features_test)

  input_data = {'title': train_title, 'body': train_body, 'answer': train_answer,
            'category_input': categorical_features_train, 'tfidf_input': train_tfidf,
            'scraped_input': train_scraped, 'numerical_input': numerical_features_train}

  cv_data = {'title': cv_title, 'body': cv_body, 'answer': cv_answer,
          'category_input': categorical_features_cv, 'tfidf_input': cv_tfidf,
           'scraped_input': cv_scraped, 'numerical_input': numerical_features_cv}

  test_data = {'title': test_title, 'body': test_body, 'answer': test_answer,
          'category_input': categorical_features_test, 'tfidf_input': test_tfidf,
          'scraped_input': test_scraped, 'numerical_input': numerical_features_test}

  return input_data, cv_data, test_data, y_train, y_cv, title_vocab_size, body_vocab_size, answer_voc
ab_size, scraped_vocab_size, embedding_matrix_title, embedding_matrix_body, embedding_matrix_answer,
embedding_matrix_scraped
```

In [31]:
```
def create_model(input_data, cv_data, test_data, y_train, y_cv, title_vocab_size, body_vocab_size, an
swer_vocab_size, scraped_vocab_size, embedding_matrix_title, embedding_matrix_body, embedding_matrix_
answer, embedding_matrix_scraped):
  K.clear_session()

  category_input = Input(64, name="category_input", dtype='float64')
  dense_category = Dense(8, activation='relu')(category_input)

  tfidf_input = Input(max_features_tfidf, name="tfidf_input", dtype='float64')
  dense_tfidf = Dense(32, activation='relu')(tfidf_input)

  numerical_input = Input(9, name="numerical_input", dtype='float64')
  dense_numerical = Dense(8, activation='relu')(numerical_input)
  ################################################
  title_input = Input(max_length_title, name="title", dtype='float64')
  title_embedding = Embedding(title_vocab_size, 300, weights=[embedding_matrix_title],
                              input_length=max_length_title, trainable=False)(title_input)
  ################################################
  body_input = Input(max_length_body, name="body", dtype='float64')
  body_embedding = Embedding(body_vocab_size, 300, weights=[embedding_matrix_body],
                              input_length=max_length_body, trainable=False)(body_input)
  ################################################
  answer_input = Input(max_length_answer, name="answer", dtype='float64')
  answer_embedding = Embedding(answer_vocab_size, 300, weights=[embedding_matrix_answer],
                              input_length=max_length_answer, trainable=False)(answer_input)
  ################################################
  scraped_input = Input(max_length_scraped, name="scraped_input", dtype='float64')
  scraped_embedding = Embedding(scraped_vocab_size, 300, weights=[embedding_matrix_scraped],
                              input_length=max_length_scraped, trainable=False)(scraped_input)
  ################################################

  concat_layer = concatenate([title_embedding, body_embedding, answer_embedding, scraped_embedding],
axis=1)

  gru_layer = CuDNNGRU(units=16, return_sequences=True, return_state=False)(concat_layer)
  avg_hidden = Flatten()(gru_layer)
  ################################################
  concat_layer_2 = concatenate([avg_hidden, dense_category, dense_tfidf, dense_numerical])
  dense_1 = Dense(64, activation='relu', kernel_initializer=tf.keras.initializers.lecun_normal(seed=1
5),
                  kernel_regularizer=regularizers.l1_l2(l1=1e-5, l2=1e-4),
                  bias_regularizer=regularizers.l2(1e-4),
```

```
                    activity_regularizer=regularizers.l2(1e-5))(concat_layer_2)

  dp = Dropout(0.1)(dense_1)

  dense_2 = Dense(30, activation='sigmoid',
                    kernel_regularizer=regularizers.l1_l2(l1=1e-5, l2=1e-4),
                    bias_regularizer=regularizers.l2(1e-4),
                    activity_regularizer=regularizers.l2(1e-5))(dp)

  model = Model(inputs=[title_input, body_input, answer_input, category_input, tfidf_input, scraped_i
nput, numerical_input], outputs=[dense_2])

  return model
```

In [32]:

```
from scipy.stats import spearmanr
import datetime

def compute_spearmanr_ignore_nan(trues, preds):
    rhos = []
    for tcol, pcol in zip(np.transpose(trues), np.transpose(preds)):
        rhos.append(spearmanr(tcol, pcol).correlation)
    return np.nanmean(rhos)

def rhos(y, y_pred):
  return tf.py_function(compute_spearmanr_ignore_nan, (y, y_pred), tf.double)
```

In [33]:

```
# After many attempts, I saw that the model achieved a maximum val_rhos of 0.31 and then the value st
arted dropping.
# To capture the best baseline model, I've used the stop_training_callback.
class stop_training_callback(tf.keras.callbacks.Callback):
  def on_epoch_end(self, epoch, logs={}):
    if(logs.get('val_rhos') > 0.31):
      self.model.stop_training = True
```

In [41]:
```
def train_model(train, test, submission, new_features_train, new_features_test):
  print('collecting preprocessed data for the model...')
  input_data, cv_data, test_data, y_train, y_cv, title_vocab_size, body_vocab_size, answer_vocab_size
, scraped_vocab_size, embedding_matrix_title, embedding_matrix_body, embedding_matrix_answer, embeddi
ng_matrix_scraped = collect_data_for_model(train, test, new_features_train, new_features_test)
  print('creating model architecture...')
  model = create_model(input_data, cv_data, test_data, y_train, y_cv, title_vocab_size, body_vocab_si
ze, answer_vocab_size, scraped_vocab_size, embedding_matrix_title, embedding_matrix_body, embedding_m
atrix_answer, embedding_matrix_scraped)

  print('model architecture created!')
  tf.keras.utils.plot_model( model, to_file='model.png', show_shapes=False,
                             show_layer_names=True, rankdir='TB', expand_nested=False, dpi=48)
  # # model.load_weights('model.hdf5')
  %reload_ext tensorboard
  !rm -rf logs
  log_dir="logs/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
  tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=log_dir, histogram_freq=1)
  stop_training = stop_training_callback()
  metrics = [rhos]
  optimizer = tf.keras.optimizers.Adam(learning_rate=0.0001)
  model_checkpoint_callback = tf.keras.callbacks.ModelCheckpoint(filepath='./drive/My Drive/model.hdf
5', save_weights_only=True, monitor='val_rhos', mode='max', save_best_only=True)
  callbacks = [tensorboard_callback, model_checkpoint_callback, stop_training]
  model.compile(loss='mean_squared_error', optimizer=optimizer, metrics=metrics)
  model.fit(input_data, y_train, epochs=20, batch_size=4, validation_data=(cv_data, y_cv), callbacks=
callbacks)

  # print('loading best baseline model weights...')
  # model.load_weights('model.hdf5')

  print('getting results for train and validation data...\n')
  y_train_pred = model.predict(input_data)
  train_rhos = compute_spearmanr_ignore_nan(y_train_pred, y_train)
  print('train_rhos:', train_rhos)
  y_cv_pred = model.predict(cv_data)
  val_rhos = compute_spearmanr_ignore_nan(y_cv_pred, y_cv)
  print('validation_rhos:', val_rhos)

  print('\npredicting the target values for test data...')
  y_test = model.predict(test_data)
  columns = submission.columns[1:]
```

```
    output = pd.DataFrame(y_test, columns=columns, index=test['qa_id'])
    output = output.reset_index()
    print('Done..!')

    return output, y_train_pred, y_cv_pred, model
```

In [42]:
```
# reading the data into dataframe using pandas
train = pd.read_csv('drive/My Drive/case_study_2/train.csv')
test = pd.read_csv('drive/My Drive/case_study_2/test.csv')
submission = pd.read_csv('drive/My Drive/case_study_2/sample_submission.csv')
new_features_test = pd.read_csv('drive/My Drive/case_study_2/new_features_test.csv')
new_features_train = pd.read_csv('drive/My Drive/case_study_2/new_features_train.csv')
```

In [43]:
```
new_features_test['upvotes'] = new_features_test['upvotes'].apply(lambda x:fix_upvotes(x))
new_features_train['upvotes'] = new_features_train['upvotes'].apply(lambda x:fix_upvotes(x))
```

In [44]:
```
print('length of new_features in last 10 percentiles')
dd = new_features_train['comments_0'] +' '+ new_features_train['answer_1'] +' '+ new_features_train[
'comment_1'] +' '+ new_features_train['answer_2'] +' '+\
      new_features_train['comment_2'] +' '+ new_features_train['answer_3'] +' '+ new_features_train[
'comment_3']
x = pd.Series([len(x.split(' ')) for x in dd])
for i in range(90,100):
  print(f'{i}% --> {x.quantile(i/100)}')
```

```
length of new_features in last 10 percentiles
90% --> 970.0
91% --> 1017.0
92% --> 1077.7600000000002
93% --> 1145.0
94% --> 1190.0
95% --> 1254.0
96% --> 1358.0
97% --> 1498.0
98% --> 1667.199999999998
99% --> 2000.7200000000066
```

In [45]:
```
max_features_tfidf = 50000
# I've defined these lengths as around 94% of all the sentences have number of words less than these
max_length_title = 26
max_length_body = 700
max_length_answer = 800
max_length_scraped = 1500
```

In [46]:
```
# Downloading GloVe data
if 'glove.6B.zip' not in os.listdir():
  !cp './drive/My Drive/glove.6B.zip' './'
  !unzip glove*.zip
```

In [47]:
```
import os
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
output, y_train_pred, y_cv_pred, model = train_model(train, test, submission, new_features_train, new
_features_test)
```

```
collecting preprocessed data for the model...


created categorical features, now loading glove vocab...

Loaded 400000 word vectors.
tokenizing the sentences of input data..

created embedding matrix for question_title...

created embedding matrix for question_body...

created embedding matrix for answer...
```

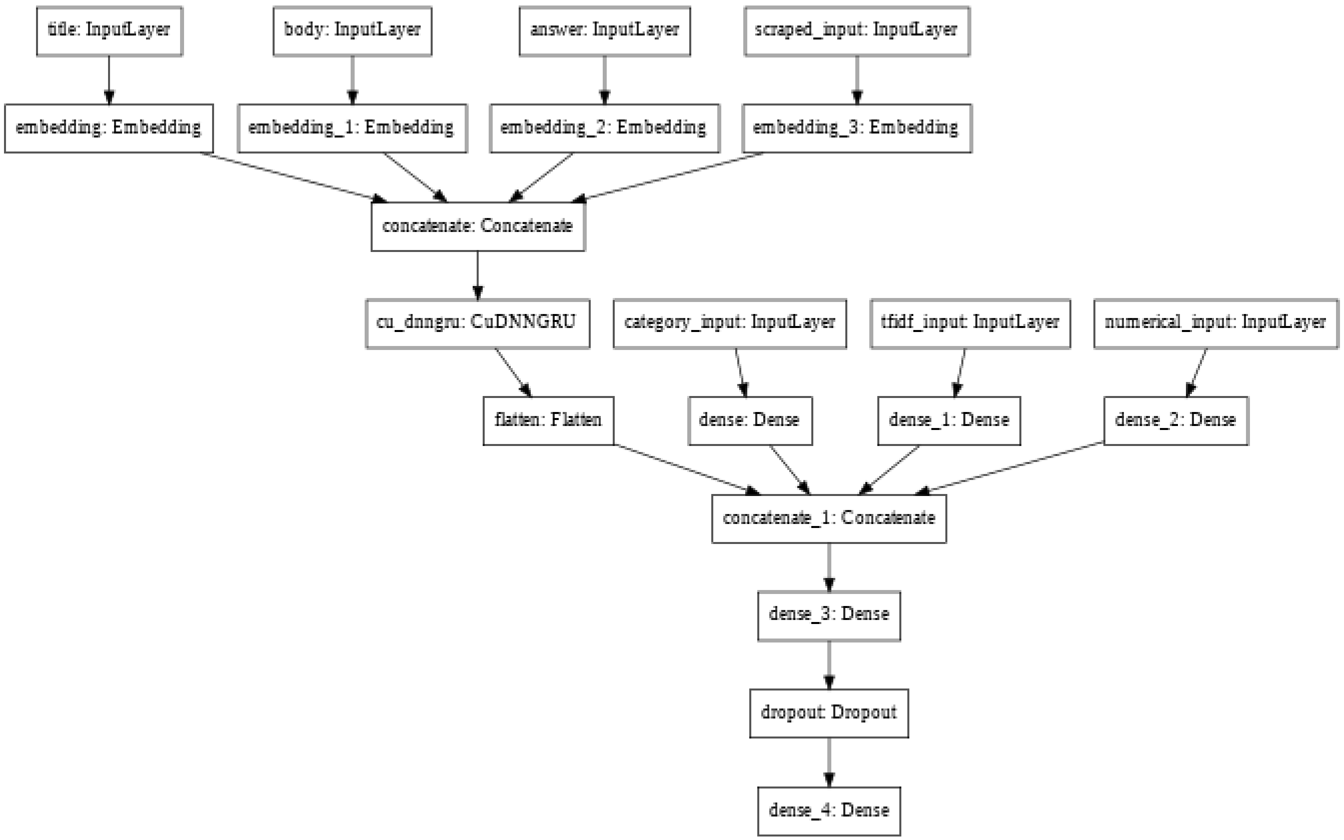
```
created embedding matrix for answer...
prepared data for tfidf now generating tfidf features...
data preprocessing completed!
creating model architecture...
model architecture created!
Epoch 1/20
1368/1368 [==============================] - 463s 338ms/step - loss: 0.0978 - rhos: 0.1240 - val_los
s: 0.0726 - val_rhos: 0.2157
Epoch 2/20
1368/1368 [==============================] - 460s 336ms/step - loss: 0.0717 - rhos: 0.2225 - val_los
s: 0.0683 - val_rhos: 0.2400
Epoch 3/20
1368/1368 [==============================] - 461s 337ms/step - loss: 0.0676 - rhos: 0.2814 - val_los
s: 0.0690 - val_rhos: 0.2681
Epoch 4/20
1368/1368 [==============================] - 461s 337ms/step - loss: 0.0656 - rhos: 0.3308 - val_los
s: 0.0679 - val_rhos: 0.2753
Epoch 5/20
1368/1368 [==============================] - 460s 337ms/step - loss: 0.0635 - rhos: 0.3599 - val_los
s: 0.0687 - val_rhos: 0.2866
Epoch 6/20
1368/1368 [==============================] - 463s 338ms/step - loss: 0.0623 - rhos: 0.3798 - val_los
s: 0.0693 - val_rhos: 0.2965
Epoch 7/20
1368/1368 [==============================] - 466s 340ms/step - loss: 0.0609 - rhos: 0.4054 - val_los
s: 0.0702 - val_rhos: 0.3006
Epoch 8/20
1368/1368 [==============================] - 463s 338ms/step - loss: 0.0603 - rhos: 0.4227 - val_los
s: 0.0703 - val_rhos: 0.3015
Epoch 9/20
1368/1368 [==============================] - 468s 342ms/step - loss: 0.0595 - rhos: 0.4347 - val_los
s: 0.0709 - val_rhos: 0.3039
Epoch 10/20
1368/1368 [==============================] - 466s 340ms/step - loss: 0.0591 - rhos: 0.4394 - val_los
s: 0.0712 - val_rhos: 0.3101
getting results for train and validation data...

train_rhos: 0.4740088539966368
validation_rhos: 0.28333251337118676

predicting the target values for test data...
Done..!
```

In [48]:
```
output.to_csv('output.csv', index=False)
```

In [ ]:
```
!kill 1105
%tensorboard --logdir logs/fit
```

In [50]:
```
tf.keras.utils.plot_model(model, to_file='model.png', show_shapes=False,
                          show_layer_names=True, rankdir='TB', expand_nested=False, dpi=48)
```

Out[50]:



In [51]:
```
model.summary()
```

```
Model: "model"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to                     
==================================================================================================
title (InputLayer)              [(None, 26)]         0                                            
__________________________________________________________________________________________________
body (InputLayer)               [(None, 700)]        0                                            
__________________________________________________________________________________________________
answer (InputLayer)             [(None, 800)]        0                                            
__________________________________________________________________________________________________
scraped_input (InputLayer)      [(None, 1500)]       0                                            
__________________________________________________________________________________________________
embedding (Embedding)           (None, 26, 300)      2096700     title[0][0]                      
__________________________________________________________________________________________________
embedding_1 (Embedding)         (None, 700, 300)     8604600     body[0][0]                       
__________________________________________________________________________________________________
embedding_2 (Embedding)         (None, 800, 300)     11856000    answer[0][0]                     
__________________________________________________________________________________________________
embedding_3 (Embedding)         (None, 1500, 300)    16330800    scraped_input[0][0]              
__________________________________________________________________________________________________
concatenate (Concatenate)       (None, 3026, 300)    0           embedding[0][0]                  
                                                                 embedding_1[0][0]                
                                                                 embedding_2[0][0]                
                                                                 embedding_3[0][0]                
__________________________________________________________________________________________________
cu_dnngru (CuDNNGRU)            (None, 3026, 16)     15264       concatenate[0][0]                
__________________________________________________________________________________________________
category_input (InputLayer)     [(None, 64)]         0                                            
__________________________________________________________________________________________________
tfidf_input (InputLayer)        [(None, 50000)]      0                                            
__________________________________________________________________________________________________
numerical_input (InputLayer)    [(None, 9)]          0                                            
__________________________________________________________________________________________________
flatten (Flatten)               (None, 48416)        0           cu_dnngru[0][0]                  
__________________________________________________________________________________________________
dense (Dense)                   (None, 8)            520         category_input[0][0]             
__________________________________________________________________________________________________
dense_1 (Dense)                 (None, 32)           1600032     tfidf_input[0][0]                
__________________________________________________________________________________________________
dense_2 (Dense)                 (None, 8)            80          numerical_input[0][0]            
__________________________________________________________________________________________________
concatenate_1 (Concatenate)     (None, 48464)        0           flatten[0][0]                    
                                                                 dense[0][0]                      
```

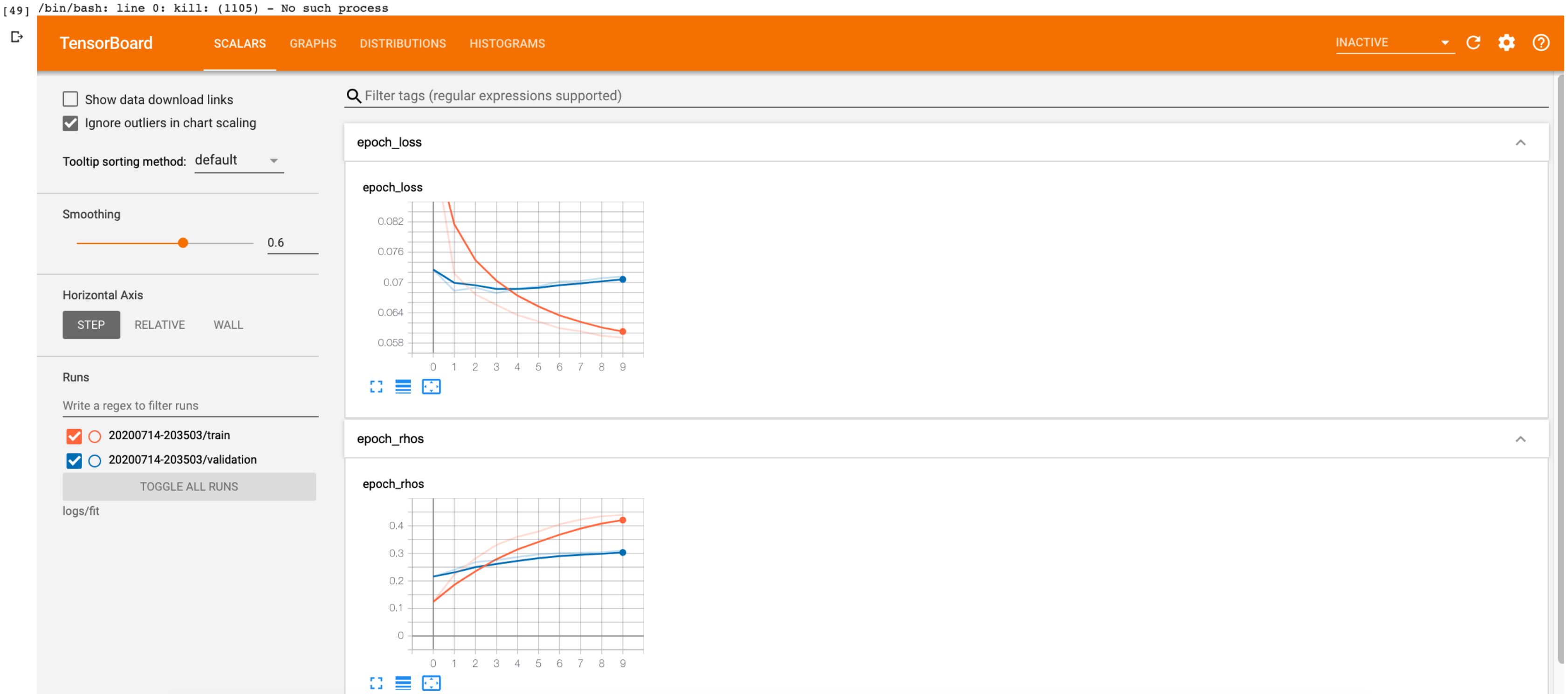
```
                                                               dense_1[0][0]
                                                               dense_2[0][0]
____________________________________________________________________________________________
dense_3 (Dense)                 (None, 64)           3101760     concatenate_1[0][0]
____________________________________________________________________________________________
dropout (Dropout)               (None, 64)           0           dense_3[0][0]
____________________________________________________________________________________________
dense_4 (Dense)                 (None, 30)           1950        dropout[0][0]
============================================================================================
Total params: 43,607,706
Trainable params: 4,719,606
Non-trainable params: 38,888,100
____________________________________________________________________________________________
```

In [52]:

```
%matplotlib inline
from IPython.display import Image
Image('1.png', width=920, height=480)
```

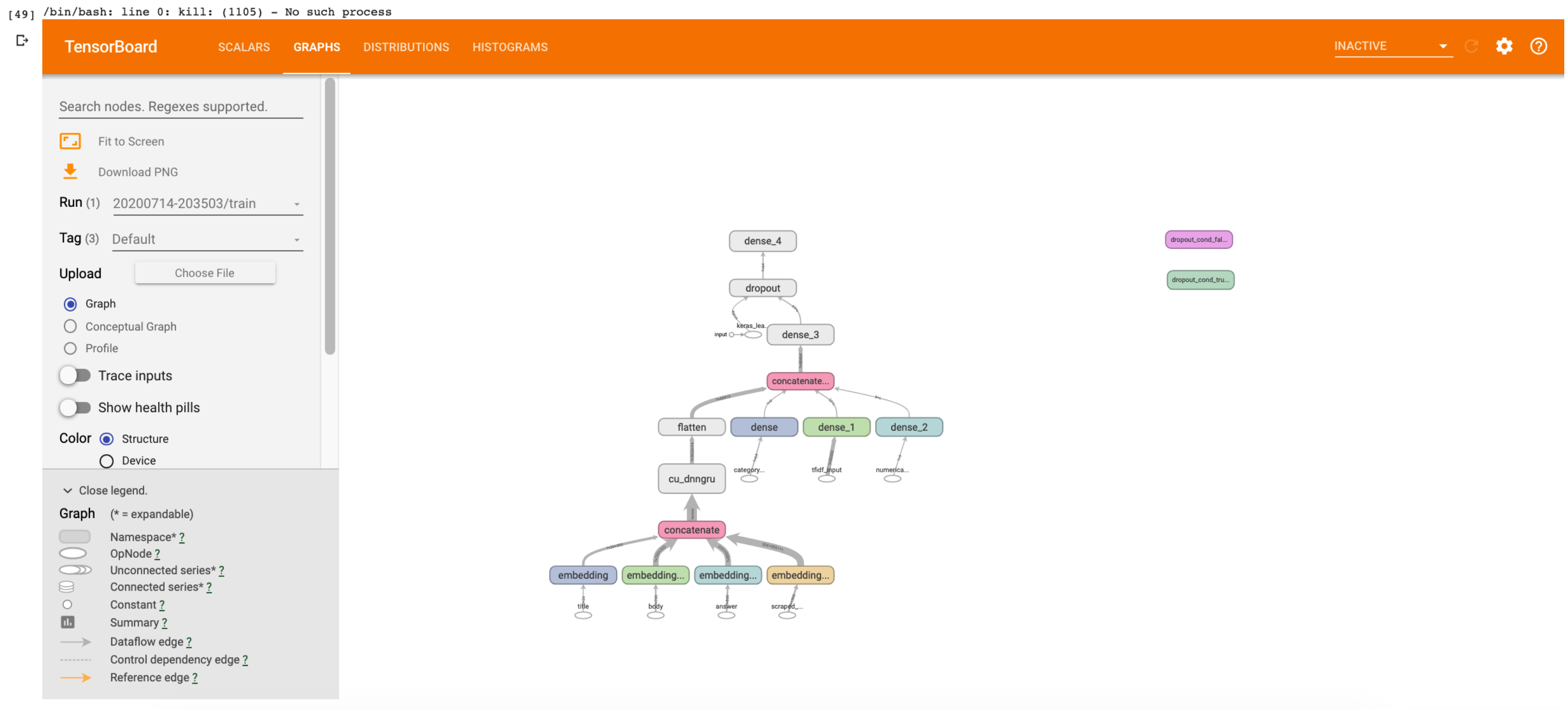
Out[52]:

```
[49] /bin/bash: line 0: kill: (1105) - No such process
```



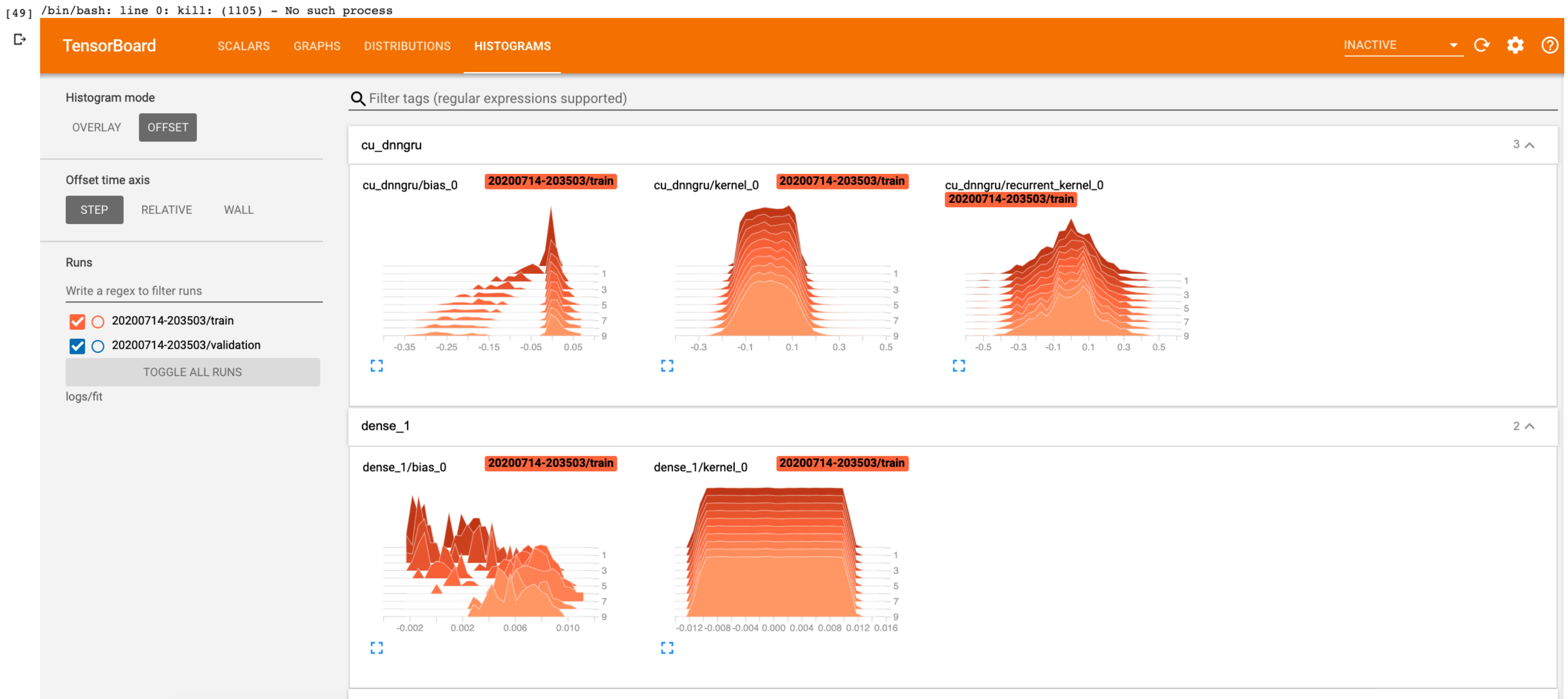
In [53]:
```
Image('2.png', width=920, height=480)
```

Out[53]:



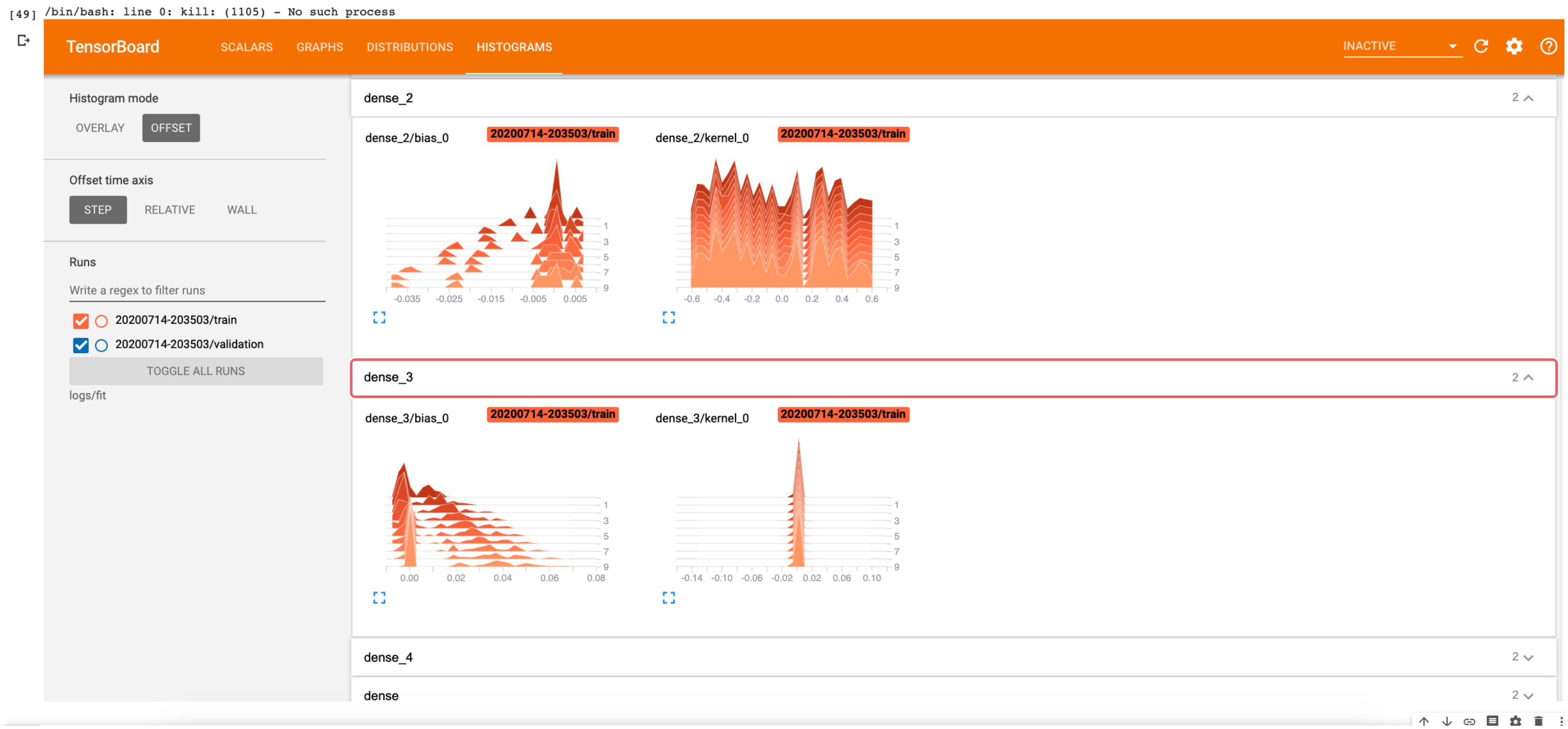
In [54]:
```
Image('3.png', width=920, height=480)
```

Out[54]:



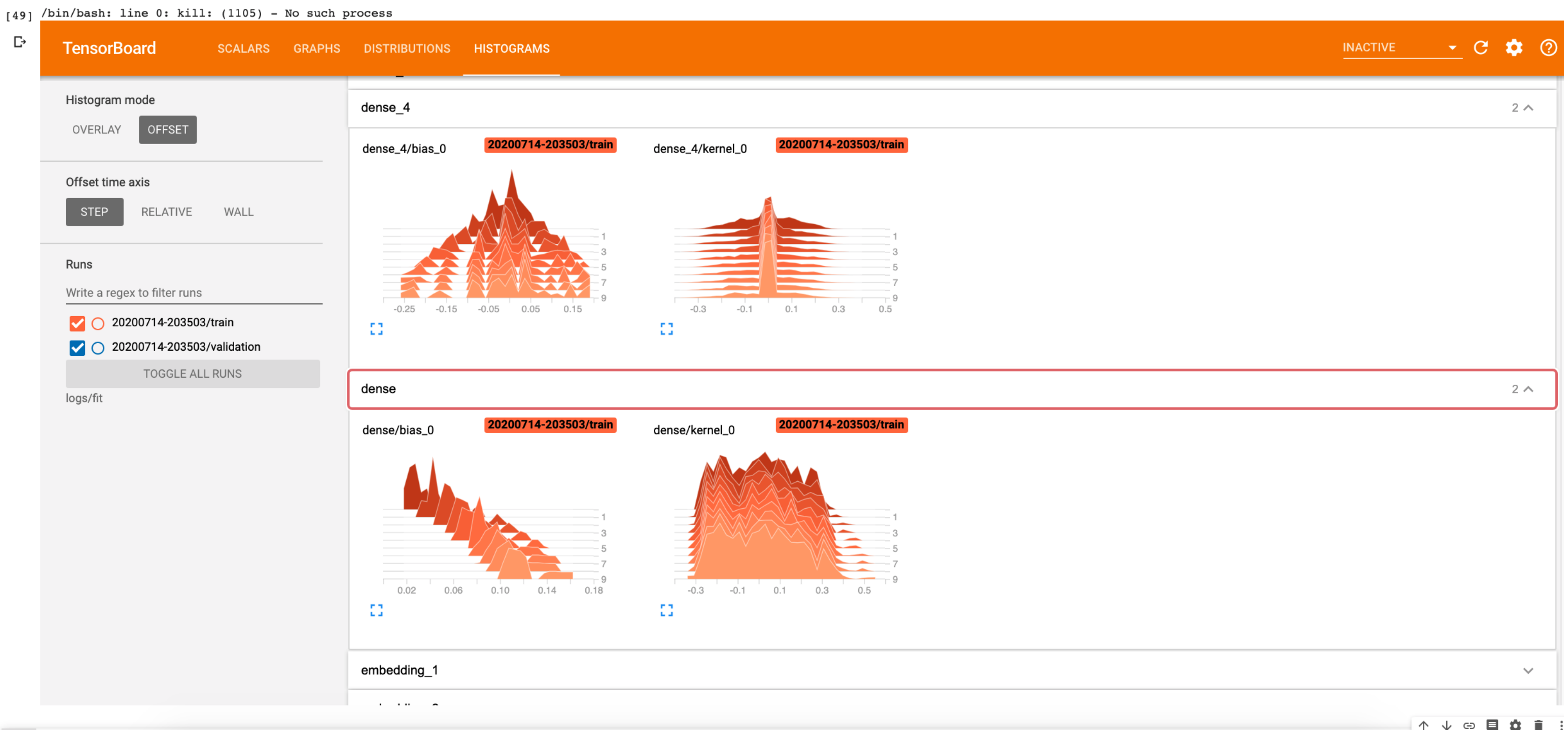
In [55]:
```
Image('4.png', width=920, height=480)
```

Out[55]:



In [56]:
```
Image('5.png', width=920, height=480)
```

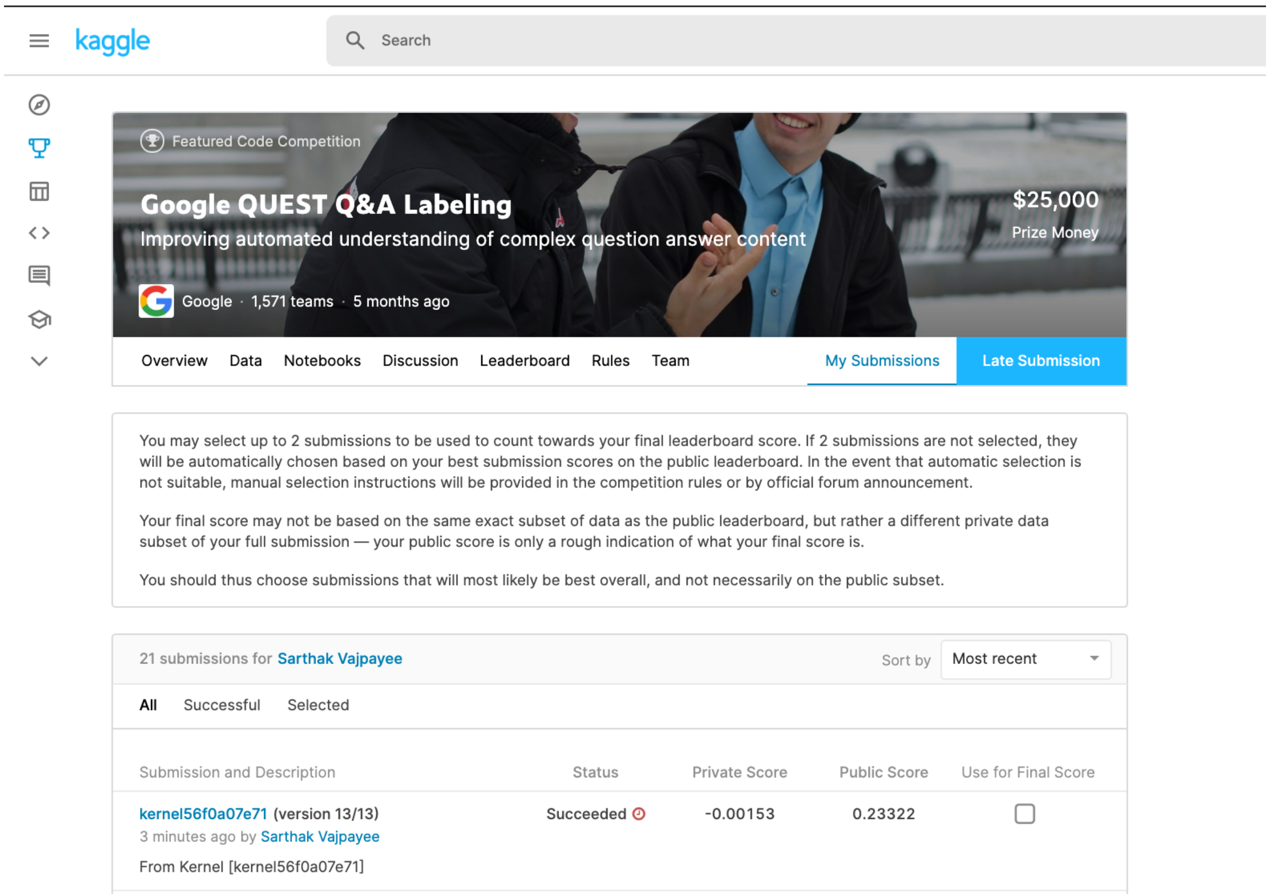
Out[56]:



We can see that the bias terms of all the GRU and dense layers are getting updated, we can see the change in the histogram of gradients as the epochs increase.

In [74]:
```
Image('score.png', width=630, height=480)
```

Out[74]:



A score of 0.23322 was generated by kaggle on the predicted values by the baseline model.

- The score is a little bit better than the previous baseline model.

In [ ]:

Post-modeling analysis

In [57]:
```
# reading the data into dataframe using pandas
train = pd.read_csv('drive/My Drive/case_study_2/train.csv')
test = pd.read_csv('drive/My Drive/case_study_2/test.csv')
submission = pd.read_csv('drive/My Drive/case_study_2/sample_submission.csv')
```

In [59]:
```
# collecting train and cv data
X_train, X_cv, y_train, y_cv = preprocess_data(train, test, new_features_train, new_features_test, fl
ag=1)
```

In [60]:
```
# Generating the log-losses for each data point in train and test data.
from sklearn.metrics import mean_squared_error
train_losses = [mean_squared_error(i,j) for i,j in zip(y_train_pred, y_train)]
cv_losses = [mean_squared_error(i,j) for i,j in zip(y_cv_pred, y_cv)]
```

In [61]:
```
# sorting the losses from minimum to maximum imdex wise.
train_loss_args = np.argsort(train_losses)
cv_loss_args = np.argsort(cv_losses)
```

We'll go through various analysis first starting with word cloud of the question_title, question_body and answer

In [64]:
```
X_train.head(3)
```

Out[64]:

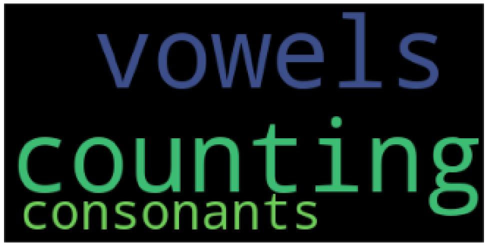
	question_title	question_body	answer	clean_url	category	upvotes	comments_0	answer_1	comment_1	answer_
2313	quantity based discount for single product in ...	i'm using latest build of expresso store , 2	we've just had the bulk discount configured to...	expressionengine	TECHNOLOGY	0		use this bulk discounts add - on , does exactl...	thanks peter . that's not going to work for us...	we've jus had th bul discour configure to.
4222	migrating a document library from sharepoint #...	i have to migrate a document library from shar...	their are 3 ways to get this done . export fro...	sharepoint	TECHNOLOGY	1		their are 3 ways to get this done . export fro...	thanks waqas , you made my day . let me try to...	for simpl migratio you ca use : ope both l.
5346	do not track header	does stack overflow honor the do not track hea...	we do not do anything special for the proposed...	meta	TECHNOLOGY	4	i understand that while you do not plan on imp...	does stack overflow honor the do not track hea...	what would you expect so to do to honour the h...	glancin at th draft spe , do nc trac only.

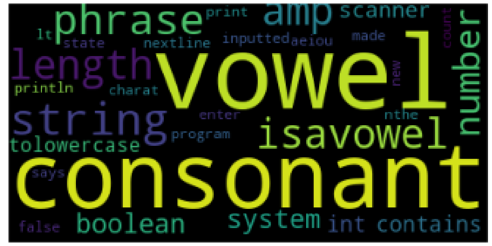
In [65]:
```
# function for generating wordcloud
from wordcloud import WordCloud, STOPWORDS
import seaborn as sns
sns.set()

def generate_wordcloud(i, data, color='black'):
  comment_words = ''
  stopwords = set(STOPWORDS)

  title_words = data['question_title'].iloc[i]
  body_words = data['question_body'].iloc[i]
  answer_words = data['answer'].iloc[i]

  title_cloud = WordCloud(width = 400, height = 200, background_color = color,
                      stopwords = stopwords, min_font_size = 10).generate(title_words)

  body_cloud = WordCloud(width = 400, height = 200, background_color = color,
                      stopwords = stopwords, min_font_size = 10).generate(body_words)

  answer_cloud = WordCloud(width = 400, height = 200, background_color = color,
                      stopwords = stopwords, min_font_size = 10).generate(answer_words)

  return title_cloud, body_cloud, answer_cloud
```

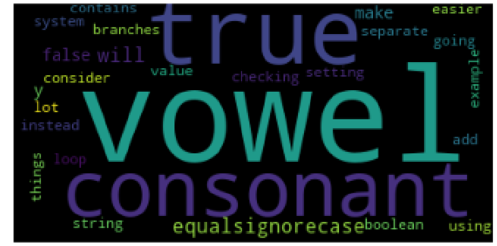
In [66]:
```
# I've picked the top 5 datapoints from train data with lowest loss and plotted the wordcloud of thei
r question_title, question_body and answer.
print('Top 5 data points from CV data that give the "lowest" loss.')
for i, idx in enumerate(train_loss_args[:5]):
  title, body, answer = generate_wordcloud(idx, X_train)
  plt.figure(figsize=(20,12))
  plt.subplot(131)
  plt.imshow(title)
  if i==0: plt.title('question_title')
  plt.ylabel(f'loss: {train_losses[idx]}')
  plt.subplot(132)
  plt.imshow(body)
  if i==0: plt.title('question_body')
  plt.subplot(133)
  plt.imshow(answer)
  if i==0: plt.title('answer')
  plt.setp(plt.gcf().get_axes(), xticks=[], yticks=[]);
  plt.show()
```

Top 5 data points from CV data that give the "lowest" loss.

loss: 0.004587648245551028







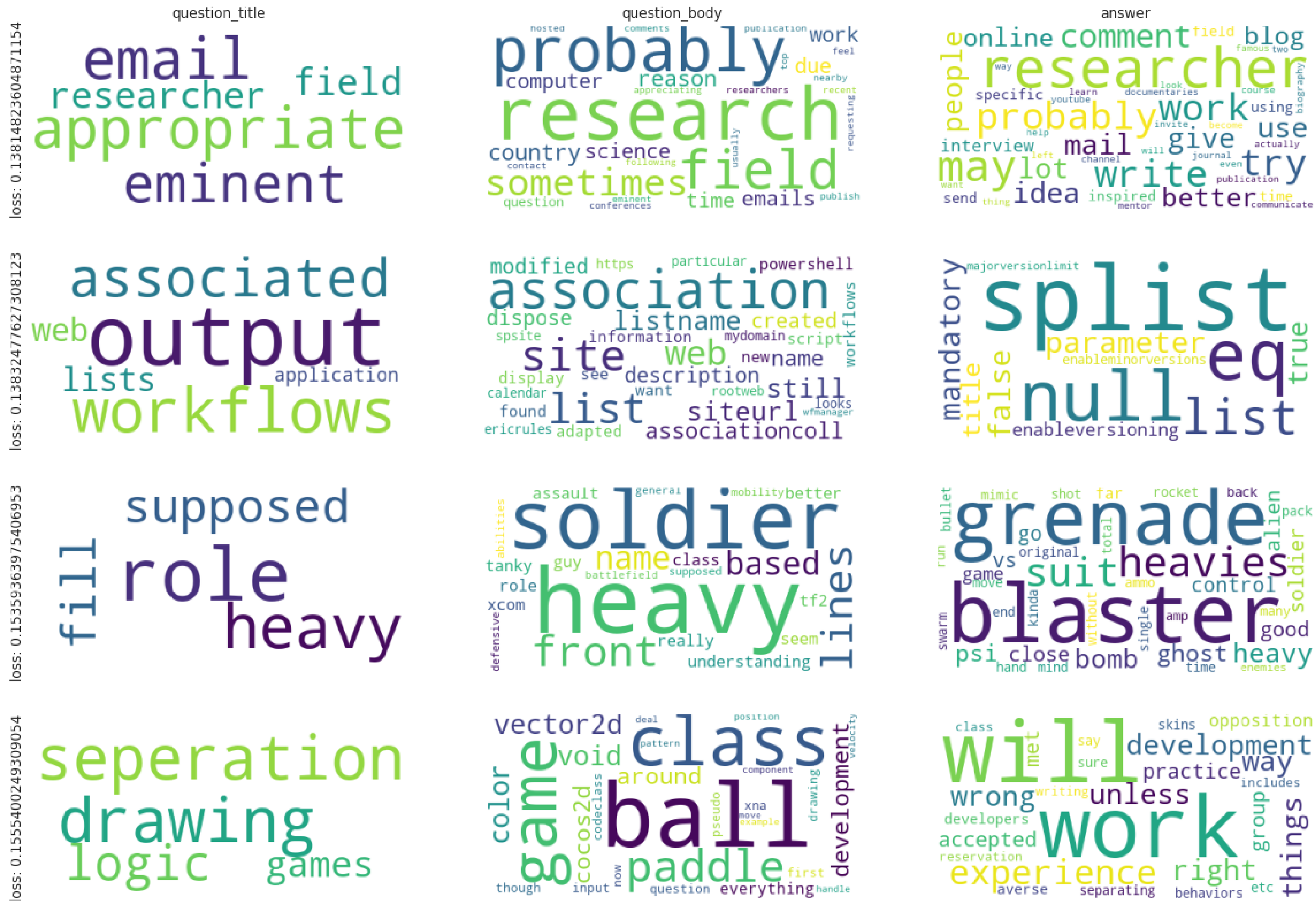
In [67]:
```
# I've picked the top 3 datapoints from cv data with lowest loss and plotted the wordcloud of their q
uestion_title, question_body and answer.
print('Top 3 data points from CV data that give the "lowest" loss.')
for i, idx in enumerate(cv_loss_args[:3]):
  title, body, answer = generate_wordcloud(idx, X_cv)
  plt.figure(figsize=(20,12))
  plt.subplot(131)
  plt.imshow(title)
  if i==0: plt.title('question_title')
  plt.ylabel(f'loss: {cv_losses[idx]}')
  plt.subplot(132)
  plt.imshow(body)
  if i==0: plt.title('question_body')
  plt.subplot(133)
  plt.imshow(answer)
  if i==0: plt.title('answer')
  plt.setp(plt.gcf().get_axes(), xticks=[], yticks=[]);
  plt.show()
```

Top 3 data points from CV data that give the "lowest" loss.

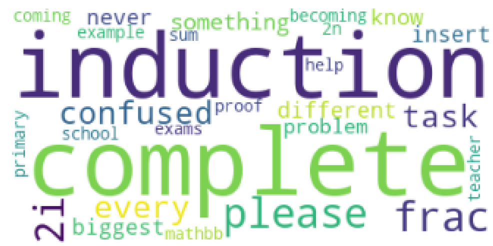
In [67]:

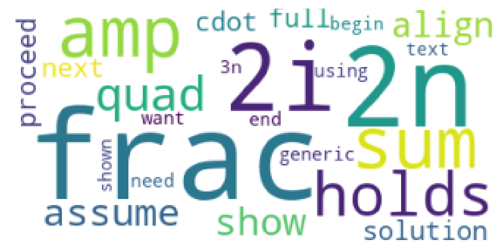
In [68]:
```
# I've picked the top 5 datapoints from train data with 'highest' loss and plotted the wordcloud of t
heir question_title, question_body and answer.
print('Top 5 data points from Train data that give the "highest" loss.')
for i, idx in enumerate(train_loss_args[-5:]):
  title, body, answer = generate_wordcloud(idx, X_train, color='white')
  plt.figure(figsize=(20,12))
  plt.subplot(131)
  plt.imshow(title)
  if i==0: plt.title('question_title')
  plt.ylabel(f'loss: {train_losses[idx]}')
  plt.subplot(132)
  plt.imshow(body)
  if i==0: plt.title('question_body')
  plt.subplot(133)
  plt.imshow(answer)
  if i==0: plt.title('answer')
  plt.setp(plt.gcf().get_axes(), xticks=[], yticks=[]);
  plt.show()
```

Top 5 data points from Train data that give the "highest" loss.



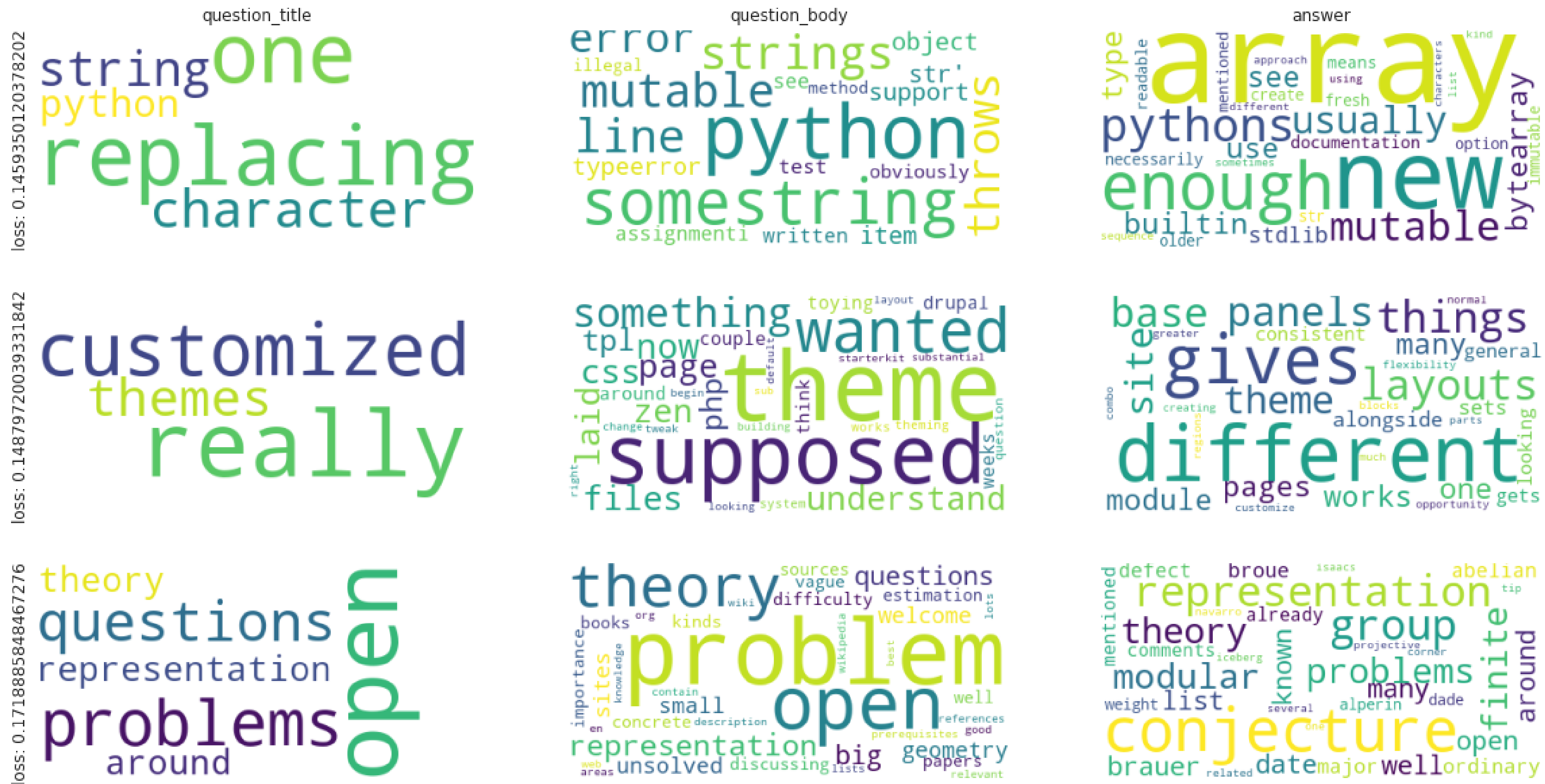

loss: 0.22455722771857498
complete
induction


coming
never
something
becoming
know
example
sum
2n
insert
induction
help
confused
proof
different
task
primary
school
exams
problem
complete
teacher
2i
every
please
frac
biggest
mathbb


proceed
amp
cdot
full
begin
align
text
next
3n
2i
using
2n
quad
want
end
frac
sum
shown
generic
need
holds
assume
show
solution

In [69]:
```
# I've picked the top 3 datapoints from train data with 'highest' loss and plotted the wordcloud of t
heir question_title, question_body and answer.
print('Top 3 data points from CV data that give the "highest" loss.')
for i, idx in enumerate(cv_loss_args[-3:]):
  title, body, answer = generate_wordcloud(idx, X_cv, color='white')
  plt.figure(figsize=(20,12))
  plt.subplot(131)
  plt.imshow(title)
  if i==0: plt.title('question_title')
  plt.ylabel(f'loss: {cv_losses[idx]}')
  plt.subplot(132)
  plt.imshow(body)
  if i==0: plt.title('question_body')
  plt.subplot(133)
  plt.imshow(answer)
  if i==0: plt.title('answer')
  plt.setp(plt.gcf().get_axes(), xticks=[], yticks=[]);
  plt.show()
```

```
Top 3 data points from CV data that give the "highest" loss.
```



Observation: Looking at the wordclouds I can say that the datapoints that lead to a good loss are more technical and mathematics oriented whereas the datapoints that lead to a bad loss are more hypothetical or non-technical. Also there are some technical question-answers (unix and web-design based) that contribute to both good and bad losses.

In [69]:

Next analysis is on the word counts in question_title, question_body and answer.

In [70]:
```
# I've picked the top 30 datapoints from train and cv data with 'lowest' loss and plotted the word co
unts of their question_title, question_body and answer.
print("word counts of the question_title, question_body and answer of top 30 train and cv data with
 'lowest' loss.")
i = 30
title_train_len = [len(l.split(' ')) for l in X_train.iloc[train_loss_args[:i]]['question_title'].val
ues]
body_train_len = [len(l.split(' ')) for l in X_train.iloc[train_loss_args[:i]]['question_body'].value
s]
answer_train_len = [len(l.split(' ')) for l in X_train.iloc[train_loss_args[:i]]['answer'].values]

title_cv_len = [len(l.split(' ')) for l in X_cv.iloc[cv_loss_args[:i]]['question_title'].values]
body_cv_len = [len(l.split(' ')) for l in X_cv.iloc[cv_loss_args[:i]]['question_body'].values]
answer_cv_len = [len(l.split(' ')) for l in X_cv.iloc[cv_loss_args[:i]]['answer'].values]

plt.figure(figsize=(20,4))
plt.subplot(131)
plt.plot(title_train_len)
plt.title('question_title (train data)')
plt.ylabel('number of words')
plt.xlabel('increasing log-loss')
plt.subplot(132)
plt.plot(body_train_len)
plt.title('question_body (train data)')
plt.xlabel('increasing log-loss')
plt.subplot(133)
plt.plot(answer_train_len)
plt.title('answer (train data)')
plt.xlabel('increasing log-loss')
# plt.setp(plt.gcf().get_axes(), xticks=[], yticks=[]);
plt.show()

plt.figure(figsize=(20,4))
plt.subplot(131)
plt.plot(title_cv_len)
plt.title('question_title (cv data)')
plt.ylabel('number of words')
plt.xlabel('increasing log-loss')
plt.subplot(132)
plt.plot(body_cv_len)
plt.title('question_body (cv data)')
plt.xlabel('increasing log-loss')
```

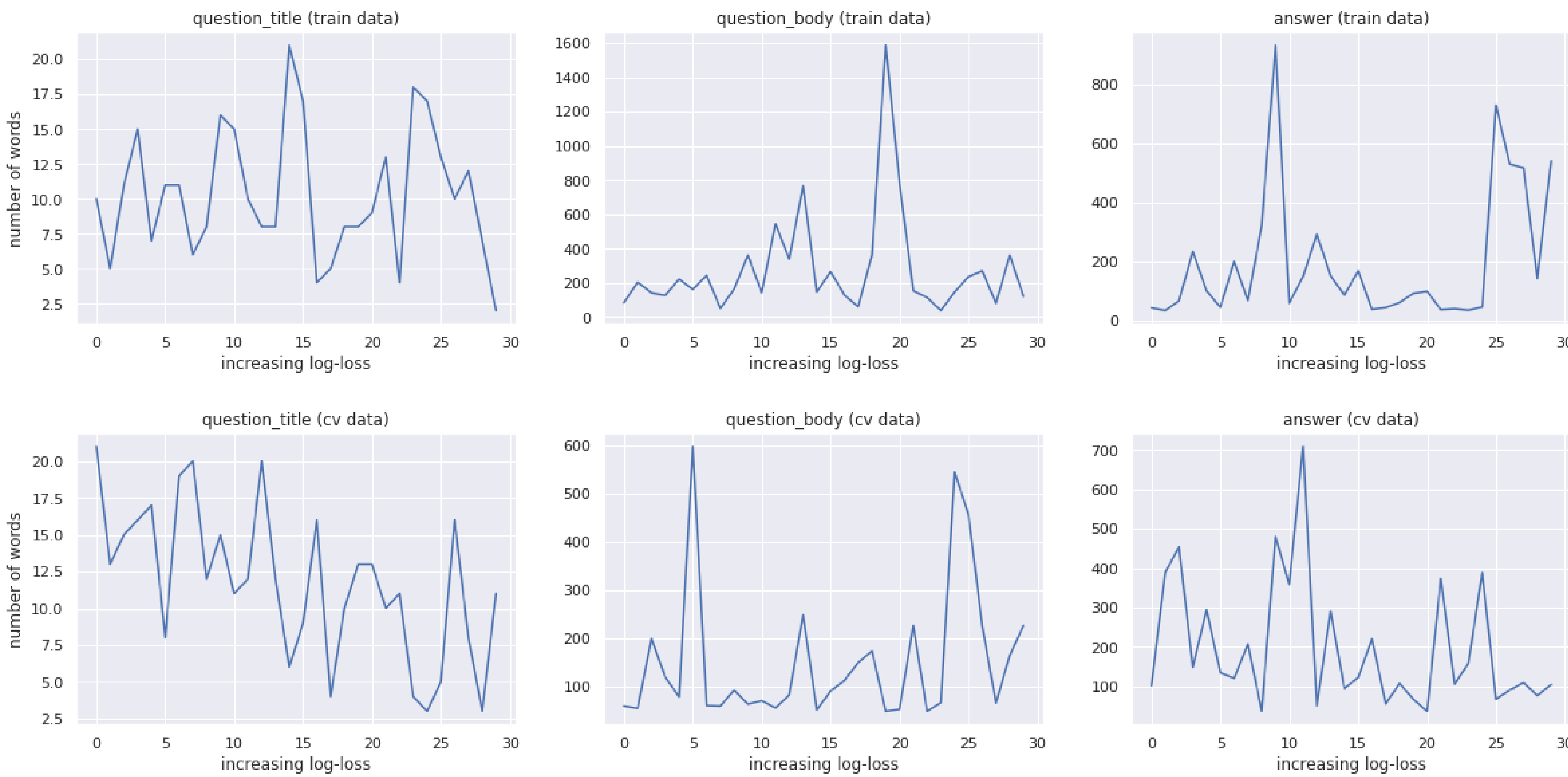
```
plt.subplot(133)
plt.plot(answer_cv_len)
plt.title('answer (cv data)')
plt.xlabel('increasing log-loss')
# plt.setp(plt.gcf().get_axes(), xticks=[], yticks=[]);
plt.show()
```

```
word counts of the question_title, question_body and answer of top 30 train and cv data with 'lowes
t' loss.
```

In [71]:
```
# I've picked the top 30 datapoints from train and cv data with 'highest' loss and plotted the word c
ounts of their question_title, question_body and answer.
print("word counts of the question_title, question_body and answer of top 30 train and cv data with
 'highest' loss.")
i = -30
title_train_len = [len(l.split(' ')) for l in X_train.iloc[train_loss_args[i:]]['question_title'].val
ues]
body_train_len = [len(l.split(' ')) for l in X_train.iloc[train_loss_args[i:]]['question_body'].value
s]
answer_train_len = [len(l.split(' ')) for l in X_train.iloc[train_loss_args[i:]]['answer'].values]

title_cv_len = [len(l.split(' ')) for l in X_cv.iloc[cv_loss_args[i:]]['question_title'].values]
body_cv_len = [len(l.split(' ')) for l in X_cv.iloc[cv_loss_args[i:]]['question_body'].values]
answer_cv_len = [len(l.split(' ')) for l in X_cv.iloc[cv_loss_args[i:]]['answer'].values]

plt.figure(figsize=(20,4))
plt.subplot(131)
plt.plot(title_train_len)
plt.title('question_title (train data)')
plt.ylabel('number of words')
plt.xlabel('increasing log-loss')
plt.subplot(132)
plt.plot(body_train_len)
plt.title('question_body (train data)')
plt.xlabel('increasing log-loss')
plt.subplot(133)
plt.plot(answer_train_len)
plt.title('answer (train data)')
plt.xlabel('increasing log-loss')
# plt.setp(plt.gcf().get_axes(), xticks=[], yticks=[]);
plt.show()

plt.figure(figsize=(20,4))
plt.subplot(131)
plt.plot(title_cv_len)
plt.title('question_title (cv data)')
plt.ylabel('number of words')
plt.xlabel('increasing log-loss')
plt.subplot(132)
plt.plot(body_cv_len)
plt.title('question_body (cv data)')
plt.xlabel('increasing log-loss')
```

```
plt.subplot(133)
plt.plot(answer_cv_len)
plt.title('answer (cv data)')
plt.xlabel('increasing log-loss')
# plt.setp(plt.gcf().get_axes(), xticks=[], yticks=[]);
plt.show()
```

```
word counts of the question_title, question_body and answer of top 30 train and cv data with 'highes
t' loss.
```



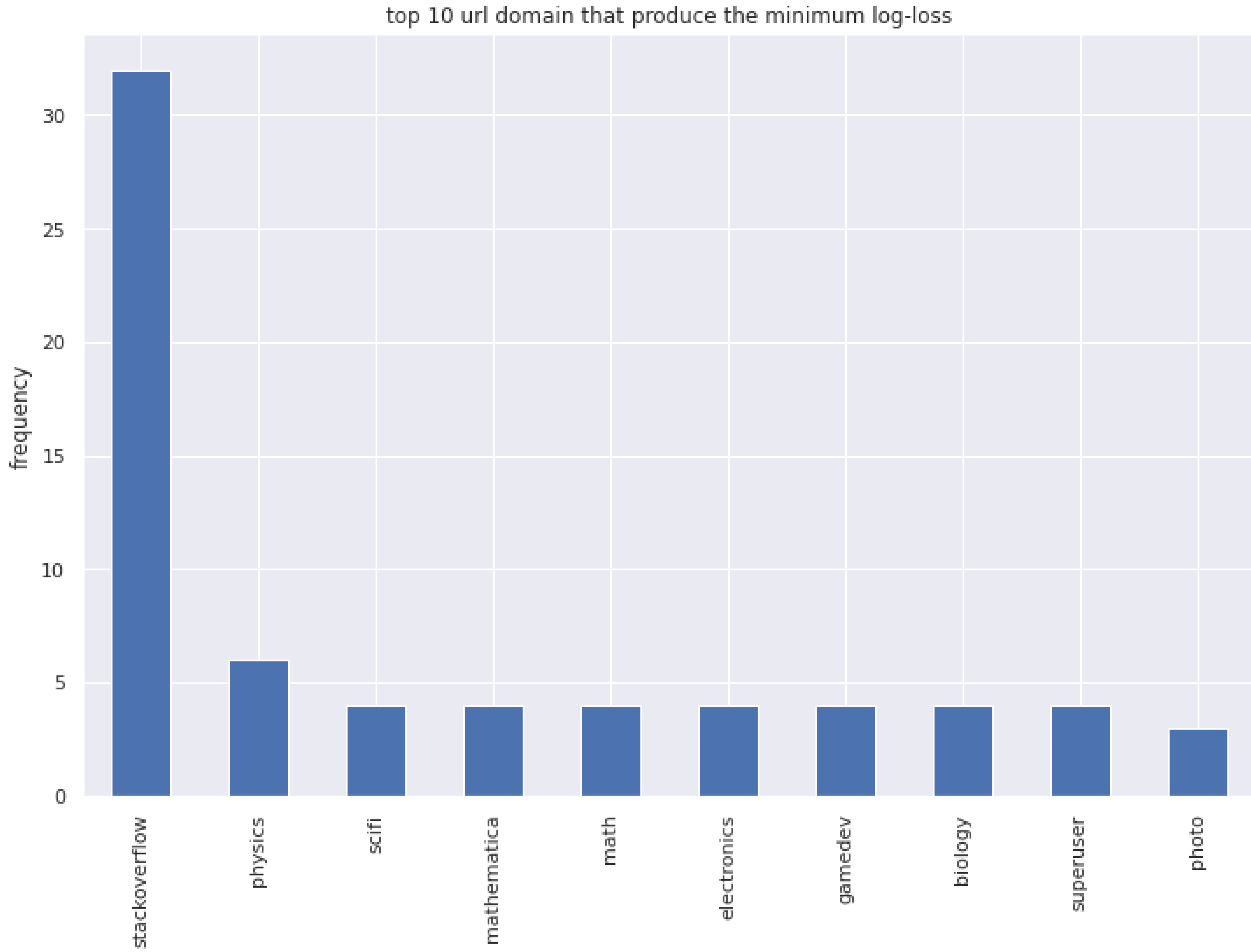
Observations: If we look at the number of words in question_title, question_body and answer we can observe that the data that generates a low loss has high number of words which means that the questions and answers are kind of thorough. So, the model does a good job when the questions and answers are detailed.

In [71]:

The next analysis is on the frequency of url domain names that lead to good or bad losses.

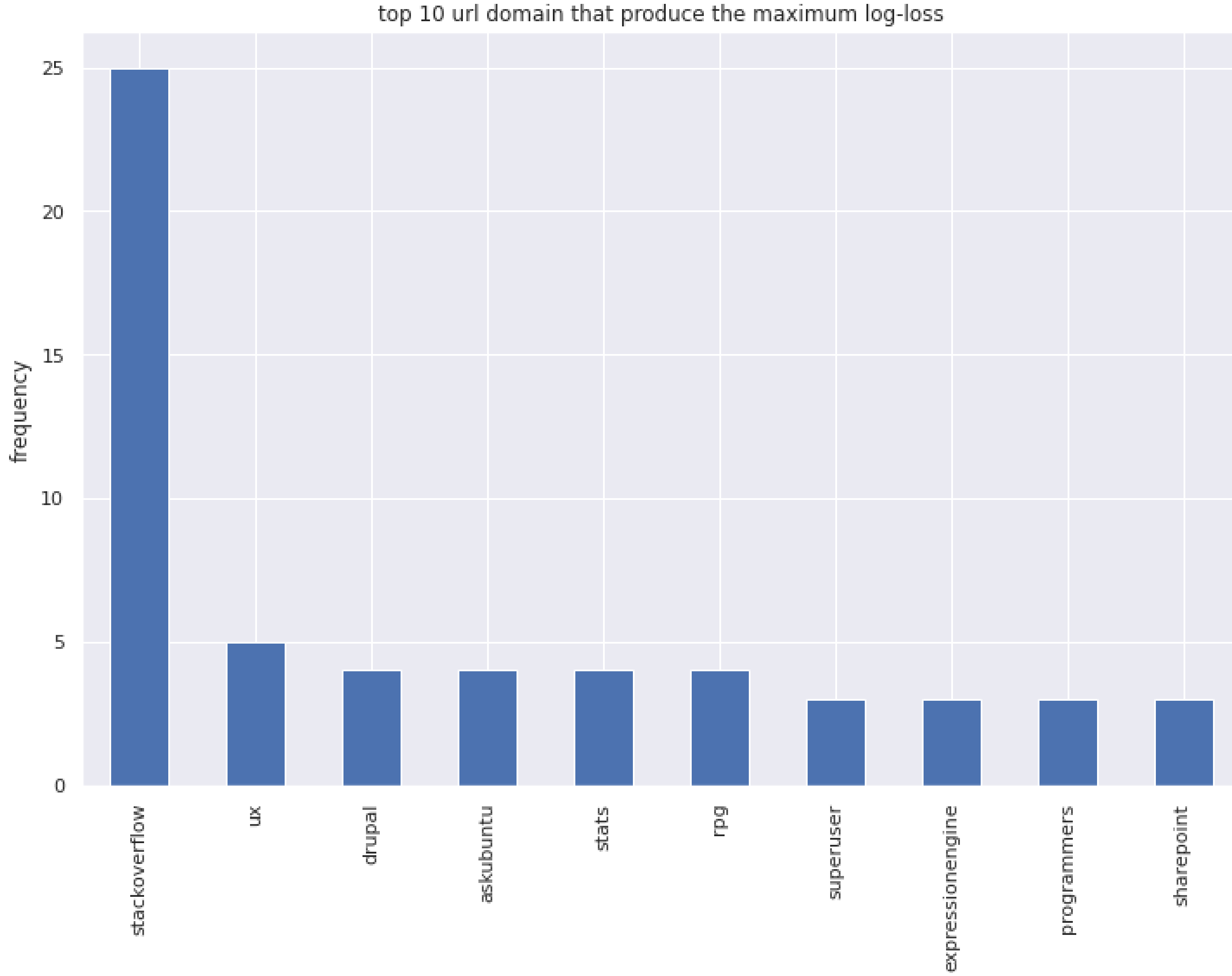
In [72]:
```
# I've picked the top 100 datapoints from train data with 'highest' loss and collected the values of
 domain names.
top_url = X_train['clean_url'].iloc[train_loss_args[:100]].value_counts()
bottom_url = X_train['clean_url'].iloc[train_loss_args[-100:]].value_counts()
```

In [73]:
```
# Top 10 frequently occuring domain names that lead to minimum loss
top_url[:10].plot.bar(figsize=(12,8))
plt.title('top 10 url domain that produce the minimum log-loss')
plt.ylabel('frequency')
plt.show()
```



In [75]:

```
# Top 10 frequently occuring domain names that lead to maximum loss
bottom_url[:10].plot.bar(figsize=(12,8))
plt.title('top 10 url domain that produce the maximum log-loss')
plt.ylabel('frequency')
plt.show()
```



Observations: We can see that there are a lot of datapoints from domain stackoverflow, physics, sci-fi that contribute to a lesser loss value whereas there are a lot of datapoints from (again) stackoverflow and ux that contribute to a higher loss.

In [75]:

```

```

The next analysis is about which domain names contribute to minimum and maximum losses

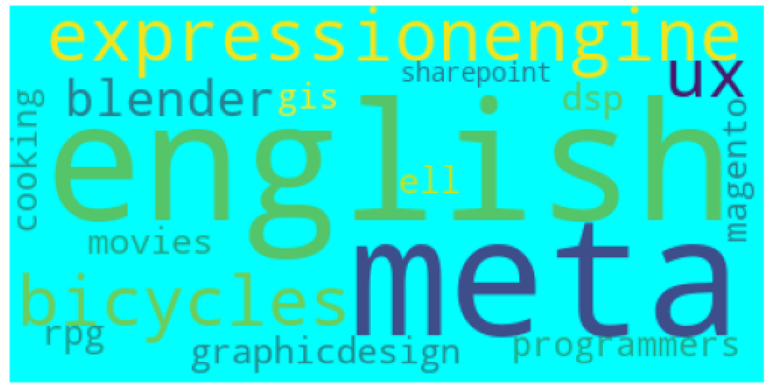
In [76]:

```
# finding the unique domain names that contribute to low and high losses
best_url = ' '.join(list(set(top_url.keys()) - set(bottom_url.keys()))) # set of urls that contribute
solely to low loss
worst_url = ' '.join(list(set(bottom_url.keys()) - set(top_url.keys()))) # set of urls that contribut
e solely to high loss
```

In [77]:
```
best_url_cloud = WordCloud(width = 400, height = 200, background_color ='orange',
                           stopwords = STOPWORDS, min_font_size = 10).generate(best_url)

worst_url_cloud = WordCloud(width = 400, height = 200, background_color ='cyan',
                            stopwords = STOPWORDS, min_font_size = 10).generate(worst_url)

plt.figure(figsize=(20,12))
plt.subplot(121)
plt.imshow(best_url_cloud)
plt.title('url domain with well predicted labels (low log-loss)')
plt.subplot(122)
plt.imshow(worst_url_cloud)
plt.title('url domain with bad predicted labels (high log-loss)')
plt.setp(plt.gcf().get_axes(), xticks=[], yticks=[]);
plt.show()
```

url domain with well predicted labels (low log-loss)

url domain with bad predicted labels (high log-loss)



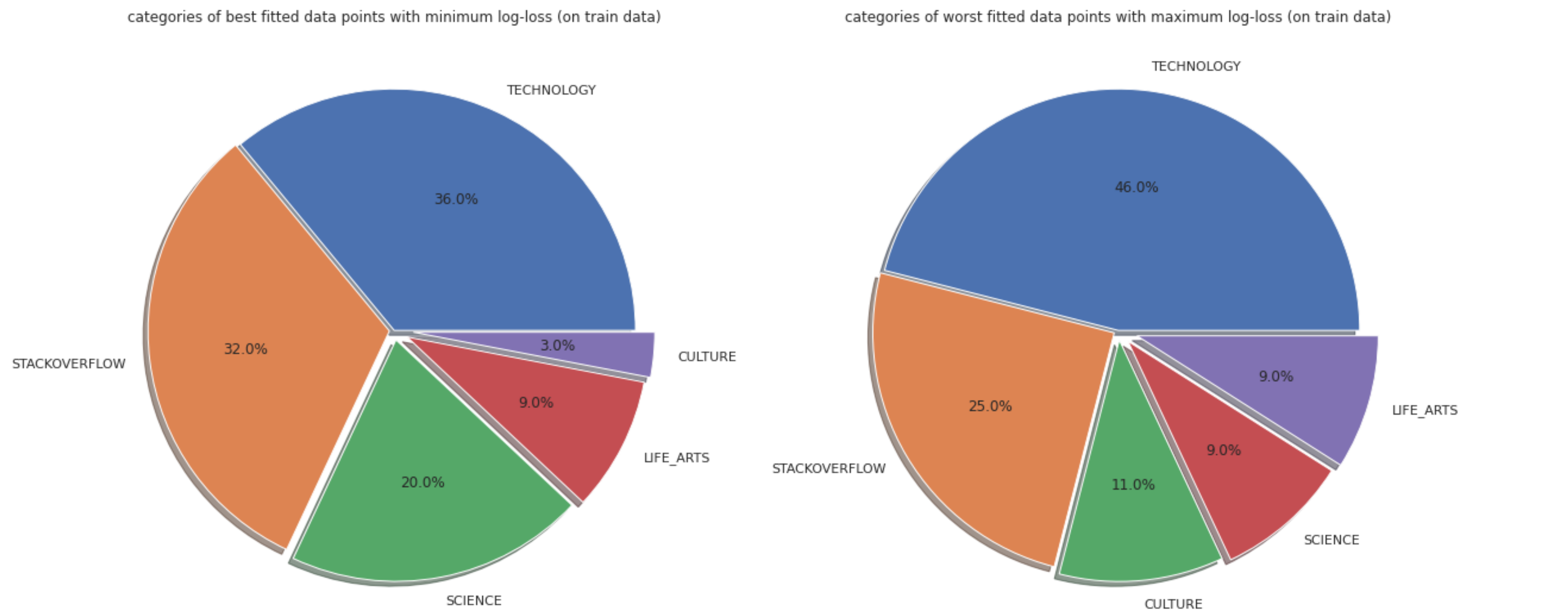
Observation: We can see that the data with science/tech like android, chemistry even scify contribute to a lower loss whereas data with non-science tags like cooking, english, movies, ux etc. contribute to a higher loss.

In [77]:

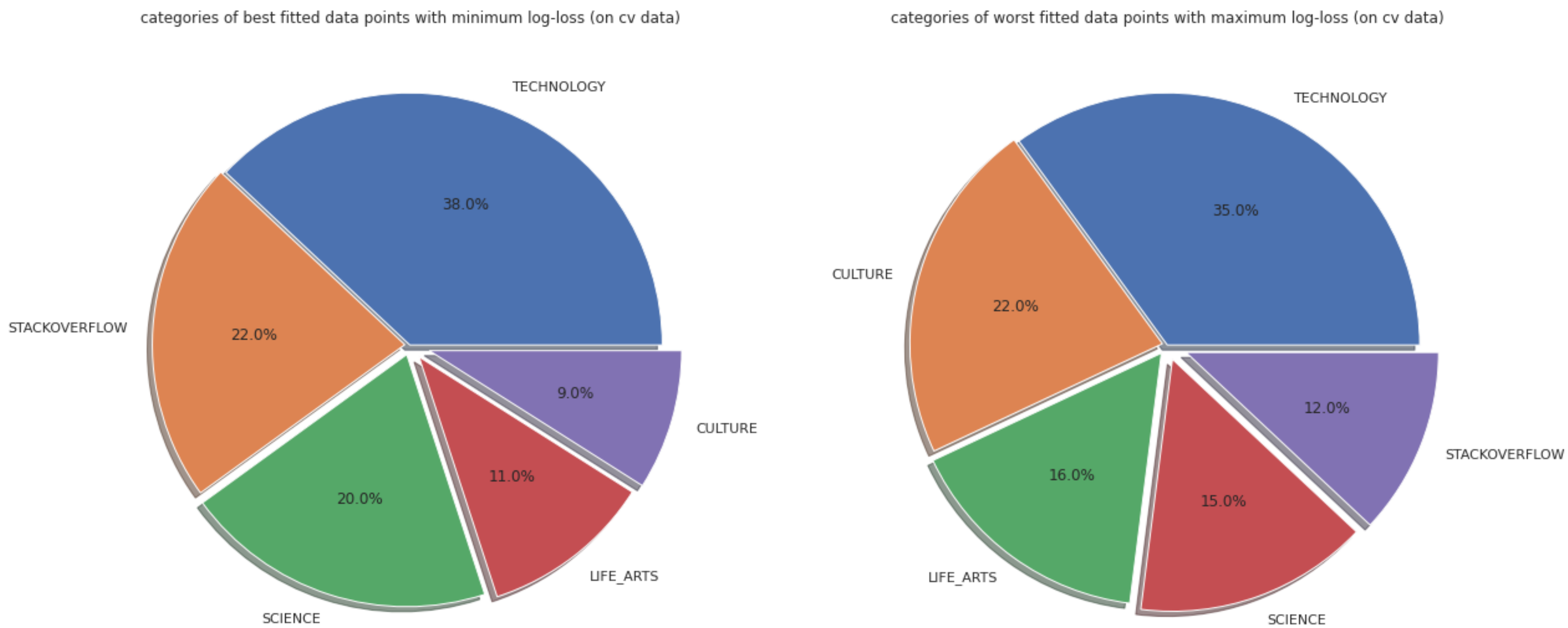
Finally let's analyze the final feature, 'category'.

For this I'll be plotting the piecharts of the categories of the top 100 data points that generate the lowest and highest loss.

In [78]:
```
# for train data
plt.figure(figsize=(20,20))
plt.subplot(121)
X_train['category'].iloc[train_loss_args[:100]].value_counts().plot.pie(autopct='%1.1f%%', explode=(0
,0.02,0.04,0.06,0.08), shadow=True)
plt.ylabel('')
plt.title('categories of best fitted data points with minimum log-loss (on train data)')
plt.subplot(122)
X_train['category'].iloc[train_loss_args[-100:]].value_counts().plot.pie(autopct='%1.1f%%', explode=(
0,0.02,0.04,0.06,0.08), shadow=True)
plt.ylabel('')
plt.title('categories of worst fitted data points with maximum log-loss (on train data)')
plt.show()
```



In [79]:
```
# for test data
plt.figure(figsize=(20,20))
plt.subplot(121)
X_cv['category'].iloc[cv_loss_args[:100]].value_counts().plot.pie(autopct='%1.1f%%', explode=(0,0.02,
0.04,0.06,0.08), shadow=True)
plt.ylabel('')
plt.title('categories of best fitted data points with minimum log-loss (on cv data)')
plt.subplot(122)
X_cv['category'].iloc[cv_loss_args[-100:]].value_counts().plot.pie(autopct='%1.1f%%', explode=(0,0.02
,0.04,0.06,0.08), shadow=True)
plt.ylabel('')
plt.title('categories of worst fitted data points with maximum log-loss (on cv data)')
plt.show()
```

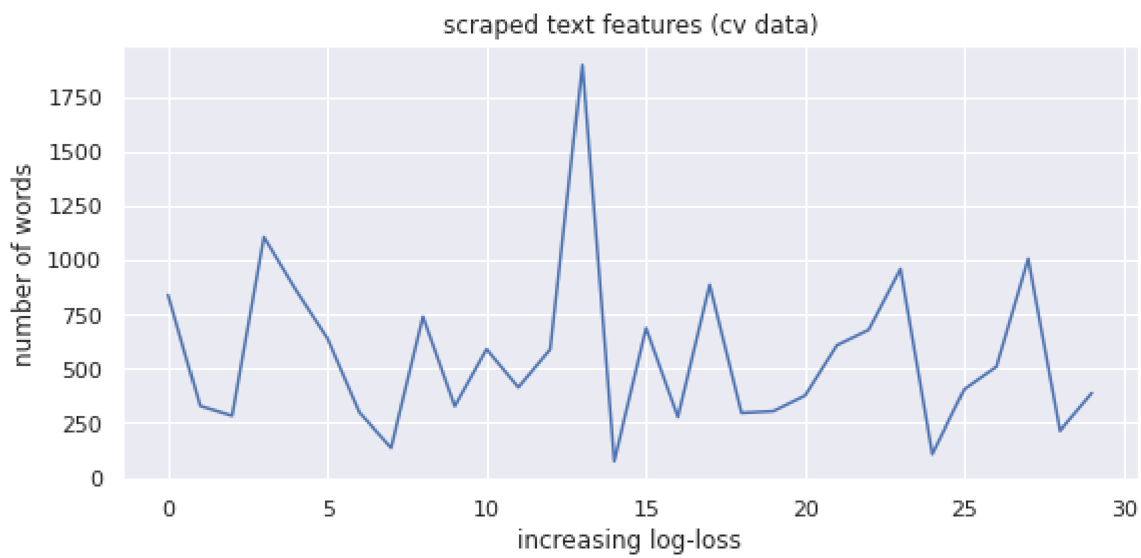


We can observe that in the top 100 points, points with category stackoverflow contributes the most to a low loss whereas lifearts and culture contribute more to a high loss. Technology and science almost contribute equally to both high and low losses.

New features

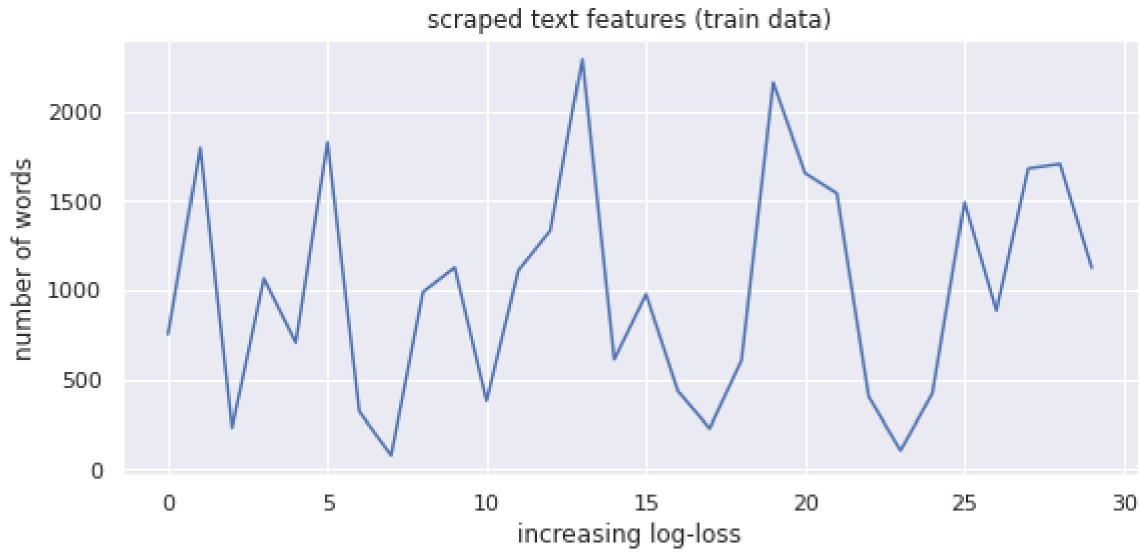
In [82]:
```
# I've picked the top 30 datapoints from train and cv data with 'lowest' loss and plotted the word co
unts of their question_title, question_body and answer.
print("word counts of the 'comments_0', 'answer_1', 'comment_1', 'answer_2','comment_2', 'answer_3',
 'comment_3' of top 30 train and cv data with 'lowest' loss.")
scraped_text_features = ['comments_0', 'answer_1', 'comment_1', 'answer_2','comment_2', 'answer_3',
'comment_3']
i = 30
scraped_train_len = [len(' '.join(l).split(' ')) for l in X_train.iloc[train_loss_args[:i]][scraped_t
ext_features].values]
scraped_cv_len = [len(' '.join(l).split(' ')) for l in X_cv.iloc[cv_loss_args[:i]][scraped_text_featu
res].values]

plt.figure(figsize=(20,4))
plt.subplot(121)
plt.plot(scraped_train_len)
plt.title('scraped text features (train data)')
plt.ylabel('number of words')
plt.xlabel('increasing log-loss')

plt.figure(figsize=(20,4))
plt.subplot(122)
plt.plot(scraped_cv_len)
plt.title('scraped text features (cv data)')
plt.ylabel('number of words')
plt.xlabel('increasing log-loss')
plt.show()
```

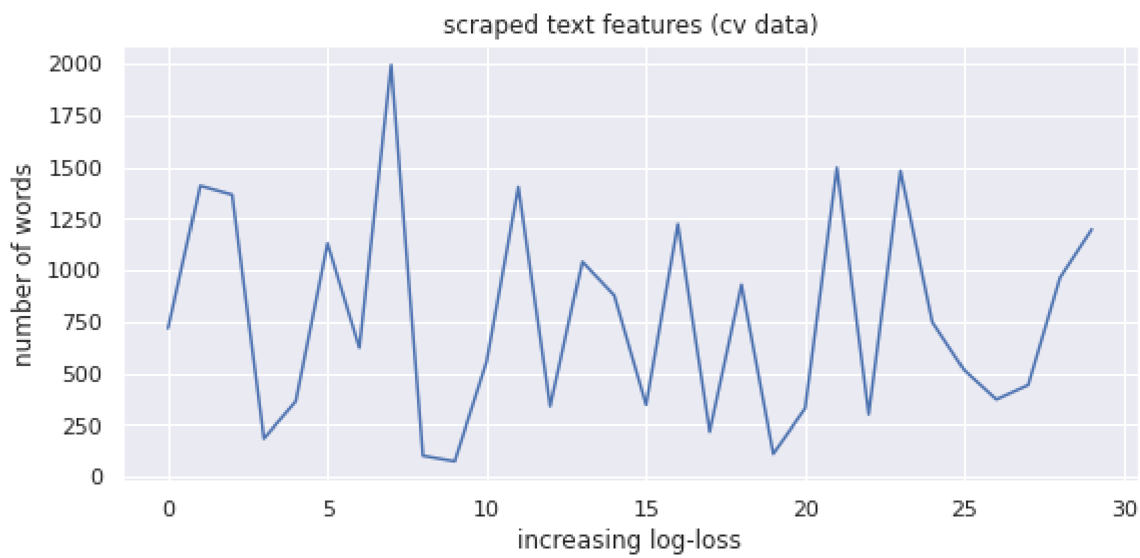
```
word counts of the 'comments_0', 'answer_1', 'comment_1', 'answer_2','comment_2', 'answer_3', 'comme
nt_3' of top 30 train and cv data with 'lowest' loss.
```



In [84]:
```
# I've picked the top 30 datapoints from train and cv data with 'lowest' loss and plotted the word co
unts of their question_title, question_body and answer.
print("word counts of the 'comments_0', 'answer_1', 'comment_1', 'answer_2','comment_2', 'answer_3',
 'comment_3' of top 30 train and cv data with 'highest' loss.")
scraped_text_features = ['comments_0', 'answer_1', 'comment_1', 'answer_2','comment_2', 'answer_3',
'comment_3']
i = -30
scraped_train_len = [len(' '.join(l).split(' ')) for l in X_train.iloc[train_loss_args[i:]][scraped_t
ext_features].values]
scraped_cv_len = [len(' '.join(l).split(' ')) for l in X_cv.iloc[cv_loss_args[i:]][scraped_text_featu
res].values]

plt.figure(figsize=(20,4))
plt.subplot(121)
plt.plot(scraped_train_len)
plt.title('scraped text features (train data)')
plt.ylabel('number of words')
plt.xlabel('increasing log-loss')

plt.figure(figsize=(20,4))
plt.subplot(122)
plt.plot(scraped_cv_len)
plt.title('scraped text features (cv data)')
plt.ylabel('number of words')
plt.xlabel('increasing log-loss')
plt.show()
```

```
word counts of the 'comments_0', 'answer_1', 'comment_1', 'answer_2','comment_2', 'answer_3', 'comme
nt_3' of top 30 train and cv data with 'highest' loss.
```

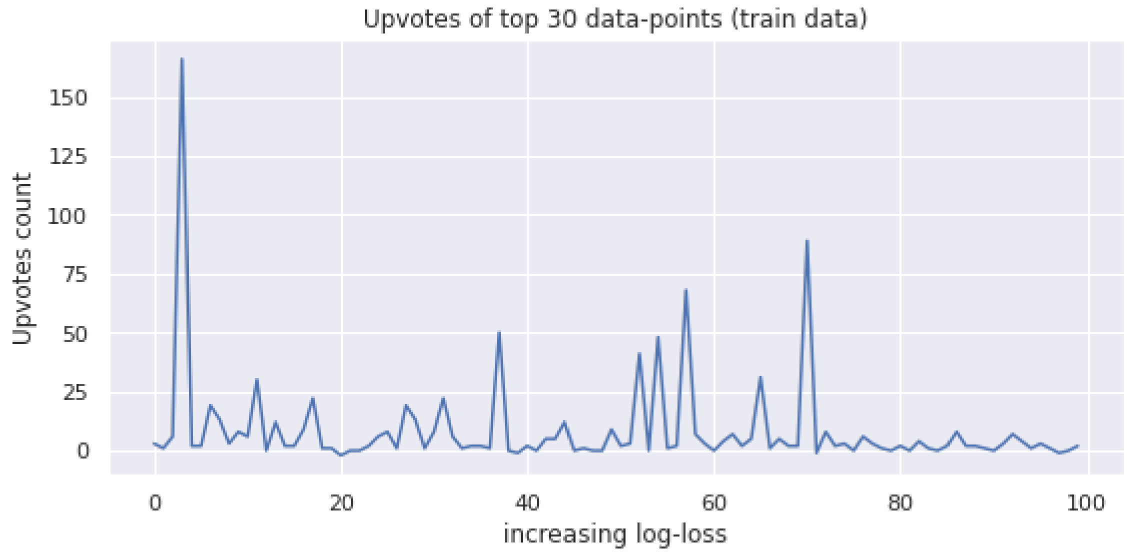


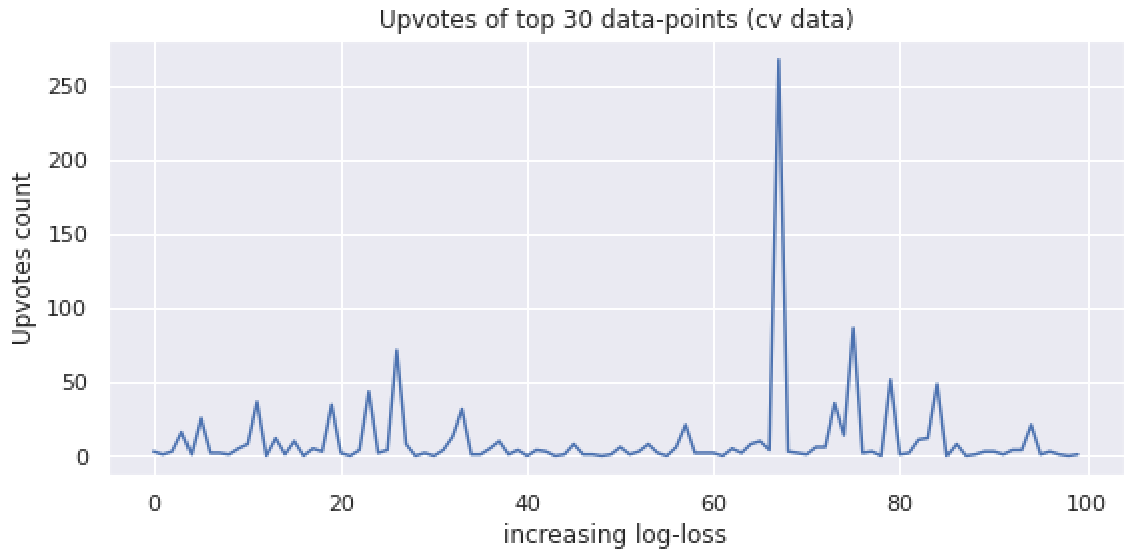


Upvotes

In [95]:
```
# I've picked the top 100 datapoints from train and cv data with 'lowest' loss and plotted the word c
ounts of their question_title, question_body and answer.
print("plot of the 'upvotes' of top 100 train and cv data with 'lowest' loss.")
i = 100
scraped_train_len = X_train.iloc[train_loss_args[:i]]['upvotes'].values
scraped_cv_len = X_cv.iloc[cv_loss_args[:i]]['upvotes'].values

plt.figure(figsize=(20,4))
plt.subplot(121)
plt.plot(scraped_train_len)
plt.title('Upvotes of top 30 data-points (train data)')
plt.ylabel('Upvotes count')
plt.xlabel('increasing log-loss')

plt.figure(figsize=(20,4))
plt.subplot(122)
plt.plot(scraped_cv_len)
plt.title('Upvotes of top 30 data-points (cv data)')
plt.ylabel('Upvotes count')
plt.xlabel('increasing log-loss')
plt.show()
```

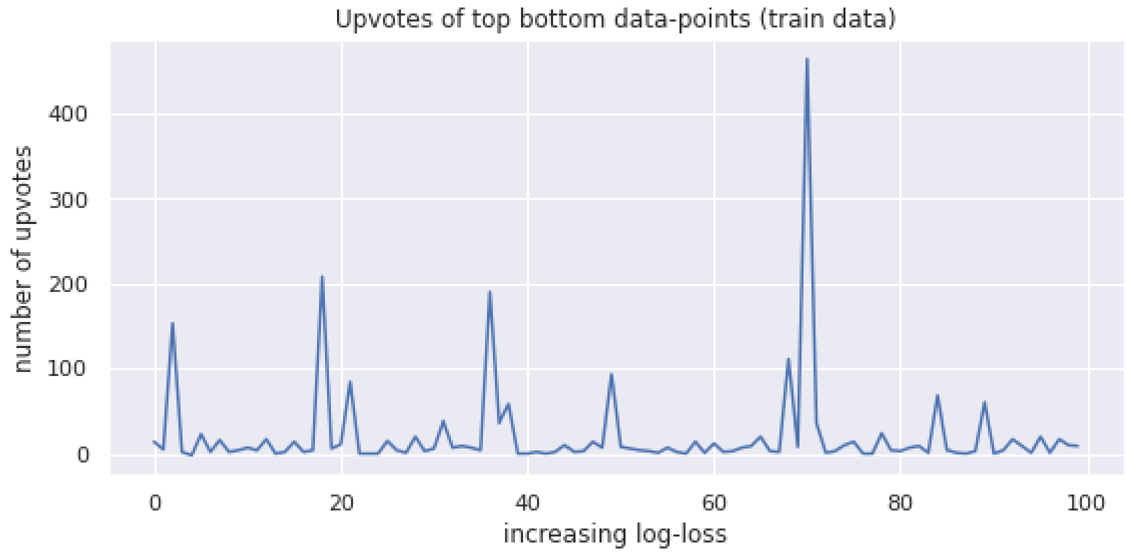
plot of the 'upvotes' of top 100 train and cv data with 'lowest' loss.

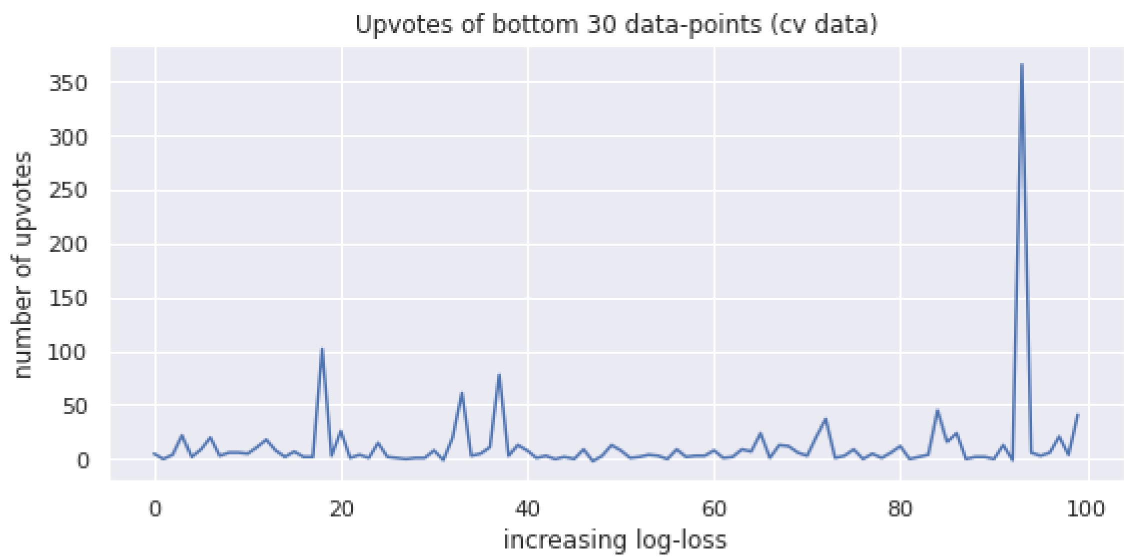




In [96]:
```
# I've picked the top 100 datapoints from train and cv data with 'lowest' loss and plotted the word c
ounts of their question_title, question_body and answer.
print("plot of the 'upvotes' of top 100 train and cv data with 'highest' loss.")
i = -100
scraped_train_len = X_train.iloc[train_loss_args[i:]]['upvotes'].values
scraped_cv_len = X_cv.iloc[cv_loss_args[i:]]['upvotes'].values

plt.figure(figsize=(20,4))
plt.subplot(121)
plt.plot(scraped_train_len)
plt.title('Upvotes of top bottom data-points (train data)')
plt.ylabel('number of upvotes')
plt.xlabel('increasing log-loss')

plt.figure(figsize=(20,4))
plt.subplot(122)
plt.plot(scraped_cv_len)
plt.title('Upvotes of bottom 30 data-points (cv data)')
plt.ylabel('number of upvotes')
plt.xlabel('increasing log-loss')
plt.show()
```

plot of the 'upvotes' of top 100 train and cv data with 'highest' loss.





We can see that the better predicted points tend to have upvotes typically between 0 and 40 whereas for the worst predicted points, the upvotes are more extreme i.e. either too low or too high.

In [ ]:

```
```

In [ ]:

```
```