In [2]:

```
from gensim.models import KeyedVectors
from gensim.test.utils import datapath
```

In [5]:

```
word_vectors = KeyedVectors.load_word2vec_format('trained_vector.txt', binary=False)
word_vectors_syn = KeyedVectors.load_word2vec_format('trained_vector_synonym.txt', b
```

In [16]:

```
word_vectors.similar_by_word("vocation")
```

Out[16]:

```
[('prerequisites', 0.8233563899993896),
 ('inclinations', 0.8157572746276855),
 ('piety', 0.8118311762809753),
 ('reverence', 0.8118261098861694),
 ('imbibed', 0.808815062046051),
 ('intellectualism', 0.806359052658081),
 ('irrevocably', 0.8047645092010498),
 ('recant', 0.7963510155677795),
 ('endeavor', 0.7948508858680725),
 ('fulfilment', 0.7947119474411011)]
```

In [17]:

```
word_vectors_syn.similar_by_word("vocation")
```

Out[17]:

```
[('career', 0.865314781665802),
 ('calling', 0.8532299399375916),
 ('Background', 0.6759084463119507),
 ('Playing', 0.6177643537521362),
 ('Coaching', 0.610306978225708),
 ('CBE', 0.609614908695221),
 ('Tamaulipas', 0.6057261228561401),
 ('Lerner', 0.5994564294815063),
 ('Cricket', 0.5841864347457886),
 ('Club', 0.5831999778747559)]
```

In [18]:

```
word_vectors.similar_by_word("advisor")
```

Out[18]:

```
[('adviser', 0.8249616622924805),
 ('economist', 0.7570538520812988),
 ('INSA', 0.7522871494293213),
 ('researcher', 0.7316626310348511),
 ('chief', 0.7193649411201477),
 ('scientist', 0.7175025939941406),
 ('statistician', 0.7067714929580688),
 ('ethnological', 0.7045462131500244),
 ('Hessa', 0.7002547979354858),
 ('Mehrishi', 0.6992570161819458)]
```

In [19]:

```
word_vectors_syn.similar_by_word("advisor")
```

Out[19]:

```
[('consultant', 0.888713002204895),
 ('adviser', 0.8387628197669983),
 ('Assistant', 0.675558865070343),
 ('Internal', 0.6680094003677368),
 ('Editor', 0.6627853512763977),
 ('Justice', 0.6615033745765686),
 ('Commerce', 0.6614713072776794),
 ('Policy', 0.658858060836792),
 ('accessory', 0.655198872089386),
 ('Clinical', 0.6520965099334717)]
```

In [20]:

```
word_vectors.similar_by_word("die")
```

Out[20]:

```
[('Sefer', 0.7002090215682983),
 ('YOU', 0.6888709664344788),
 ('Bhagavad', 0.6852923631668091),
 ('Vendôme', 0.6836792826652527),
 ('nicht', 0.6787155270576477),
 ('Kirche', 0.6786268949508667),
 ('Bingen', 0.6768293380737305),
 ('ba', 0.6744521260261536),
 ('Adda', 0.6736612319946289),
 ('Rijn', 0.6681785583496094)]
```

In [21]:

```
word_vectors_syn.similar_by_word("die")
```

Out[21]:

```
[('perish', 0.846362829208374),
 ('exit', 0.8302855491638184),
 ('expire', 0.7911310195922852),
 ('choke', 0.7716532349586487),
 ('Nibelungen', 0.7007843255996704),
 ('Bodyline', 0.6602303981781006),
 ('Krejčíková', 0.6550697088241577),
 ('Uma', 0.6495055556297302),
 ('dreary', 0.6426095962524414),
 ('if', 0.6351494789123535)]
```

In [22]:

```
word_vectors.similar_by_word("ten")
```

Out[22]:

```
[('forty', 0.839396595954895),
 ('five', 0.7634023427963257),
 ('nineteen', 0.7439690828323364),
 ('two', 0.7439565658569336),
 ('twelve', 0.7374639511108398),
 ('fifteen', 0.7328503131866455),
 ('eighty', 0.7328100204467773),
 ('eleven', 0.7300284504890442),
 ('fourteen', 0.7289317846298218),
 ('six', 0.7285114526748657)]
```

In [23]:

```
word_vectors_syn.similar_by_word("ten")
```

Out[23]:

```
[('decade', 0.8107796311378479),
 ('10', 0.7953133583068848),
 ('719', 0.7661923170089722),
 ('6', 0.7541136145591736),
 ('348', 0.7443172931671143),
 ('237', 0.738518476486206),
 ('11', 0.7367497086524963),
 ('258', 0.7311567068099976),
 ('285', 0.730393648147583),
 ('670', 0.7301467657089233)]
```

In [24]:

```
word_vectors.similar_by_word("however")
```

Out[24]:

```
[('Bucer', 0.7610359191894531),
 ('Sertorius', 0.7558284401893616),
 ('Nurhaci', 0.7505505084991455),
 ('alms', 0.7501428127288818),
 ('virginity', 0.7496191263198853),
 ('stammer', 0.7477184534072876),
 ('Arianism', 0.7467020750045776),
 ('unfounded', 0.7456619739532471),
 ('bargains', 0.7444959878921509),
 ('Arius', 0.7433899641036987)]
```

In [25]:

```
word_vectors_syn.similar_by_word("however")
```

Out[25]:

```
[('nonetheless', 0.7945919036865234),
 ('nevertheless', 0.7935124039649963),
 ('notwithstanding', 0.7898233532905579),
 ('yet', 0.7674560546875),
 ('stutter', 0.7492031455039978),
 ('stammer', 0.744091808795929),
 ('imperious', 0.7124859094619751),
 ('Yamaguchi', 0.7095609903335571),
 ('unsavory', 0.7061512470245361),
 ('disturbed', 0.7060285806655884)]
```

I have chosen some frequent words appearing in the 'synonyms.txt'. From the result, I think that the new model gives more reasonable nearest neighbours. It is because the nearest neighbours of these words according to the new model are mostly its synonyms, while according to the original model, it is hard to find any pattern or rule in the neighboring words.