NAMES:

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In [1]:
```
from datetime import datetime
from time import time
import pandas as pd
import numpy as np
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from nltk.corpus import stopwords  #pip install nltk
from nltk.corpus import stopwords
import nltk
nltk.download("stopwords")
from nltk.stem.porter import PorterStemmer
import string
from sklearn.metrics.pairwise import cosine_similarity, euclidean_distances
from gensim.models import word2vec  #pip install word2vec
from wordcloud import WordCloud  #pip install wordcloud
import sqlite3
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import re
from sklearn.manifold import TSNE, MDS
from sklearn.decomposition import NMF, LatentDirichletAllocation
from textblob import TextBlob  #Sentiment Analysis - pip install textblob
from sklearn.decomposition import TruncatedSVD, NMF
import matplotlib.patches as mpatches
import matplotlib
path_to_csv = '../../../cs82_advanced_machine_learning_data/HW2/papers.csv'
```

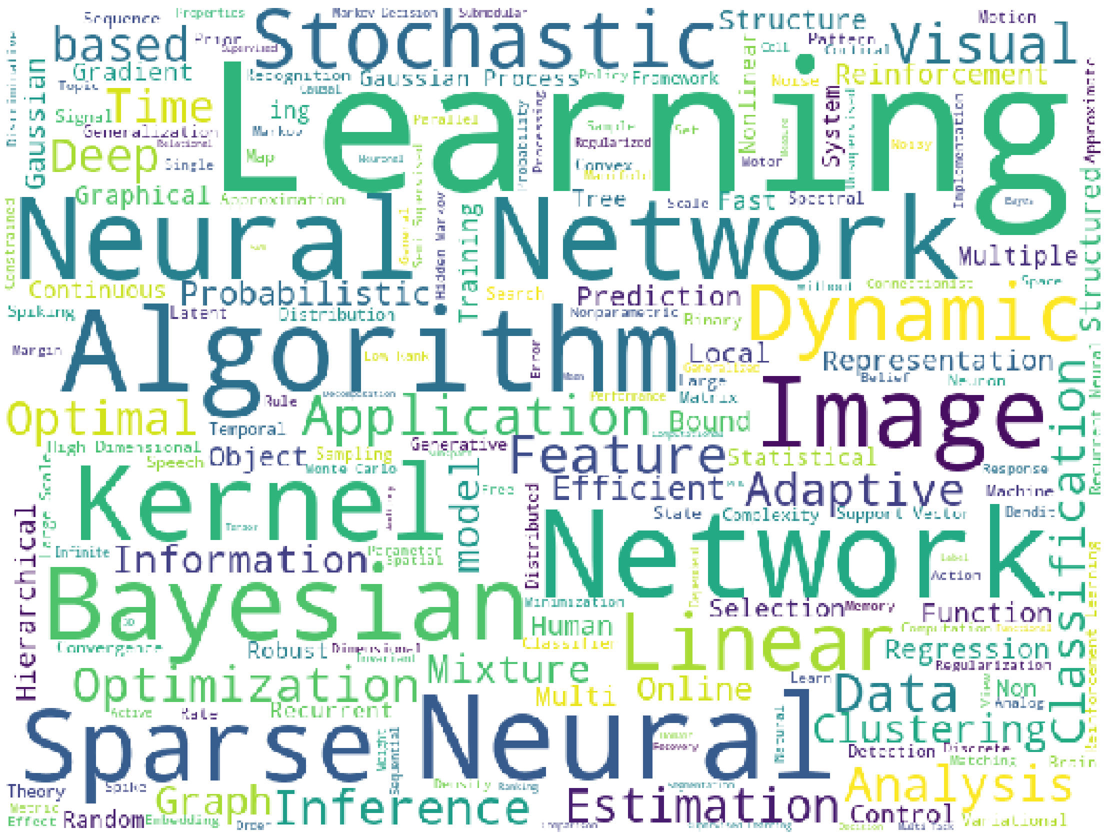
```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\khan_\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

```
C:\ProgramData\Anaconda3\lib\site-packages\gensim\utils.py:1197: UserWarning:
detected Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

1. Plotting a word cloud to get an idea of the important words

In [2]:
```
# READ CSV
papers = pd.read_csv(path_to_csv)
features=['title']
papers=papers.loc[:,features]

# REMOVE UNDESIRED WORDS FROM THE DATA
undesired_words = ['Abstract Missing', 'Using', 'using', "New", "Based", 'Use'
, 'Method', 'Used',
                   'Problem', 'Approach', 'Model', 'Models', 'via']
for word in undesired_words:
    papers['title'] = papers['title'].str.replace(word,'')


papers=papers.sample(frac=1,random_state=0)
train_qs = pd.Series(papers['title'].tolist()).astype(str)

qs_text = "".join(train_qs)

cloud =WordCloud(font_path=None, width=800, height=600, margin=2, ranks_only=N
one,
                 prefer_horizontal=0.9, mask=None, scale=1, color_func=None, m
ax_words=200,
                 min_font_size=4, stopwords=None, random_state=None, backgroun
d_color='white',
                 max_font_size=None, font_step=1, mode='RGB', relative_scaling
=.5, regexp=None,
                 collocations=True, colormap=None, normalize_plurals=bool, con
tour_width=0,
                 contour_color='black', repeat=None).generate(str(qs_text))
print(cloud)
plt.figure(figsize=(14,8))
plt.imshow(cloud);
plt.axis('off');
#Word Clouds on a image - https://github.com/amueller/word_cloud/blob/master/e
xamples/alice_colored.png
```

```
<wordcloud.wordcloud.WordCloud object at 0x000001CDD0C26B00>
```

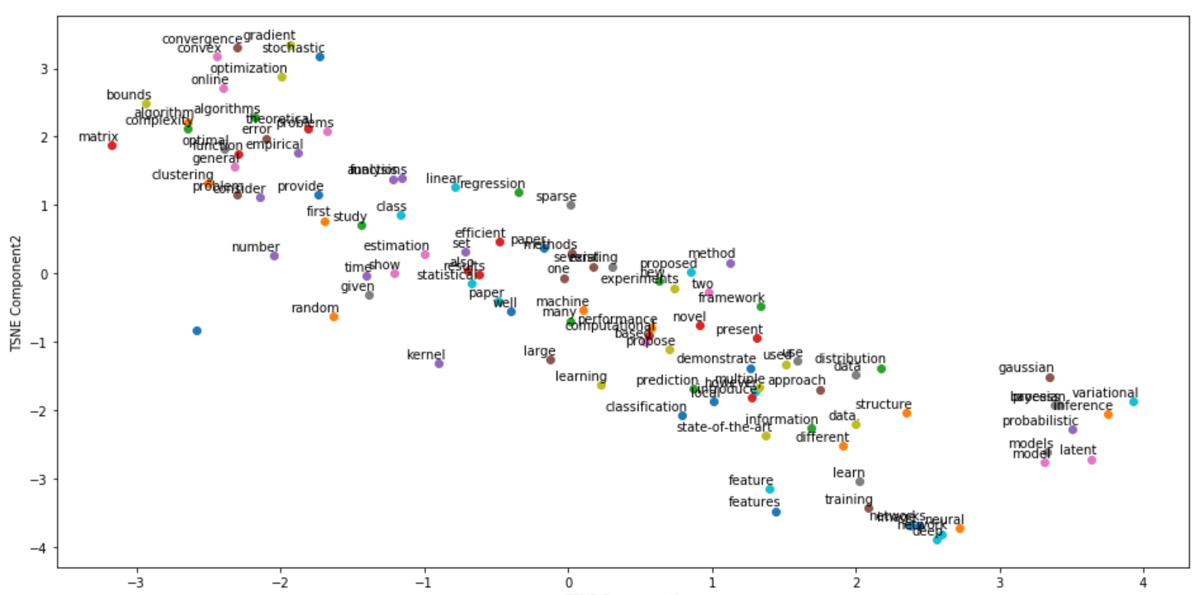


2. Running t-SNE model and plot to try to find clusters of terms that would help determine topic names.

We looked at the titles and abstract of each paper and converted them to word2vec matrices. We then reduced them to 2 dimensions using tsne and plotted the 2 tsne components to see if related words cluster together.

In [3]:
```
#For t-SNE model and plot, we have considered papers "title" and papers "abstr
act".
papers = pd.read_csv(path_to_csv)
features=['title','abstract']

#Removing undesired words that have been used frequently in the papers "abstra
ct".
for word in undesired_words:
    papers['abstract'] = papers['abstract'].str.replace(word,'')

papers=papers.loc[:,features]
papers.loc[:,'title'] = papers.title.apply(lambda x: x.lower())
papers.loc[:,'abstract'] = papers.abstract.apply(lambda x: x.lower())

#Remove chars that are not letters or numbers
regex = re.compile('\n')
papers.loc[:,'title'] = papers.title.apply(lambda x: regex.sub(' ',x))
papers.loc[:,'abstract'] = papers.abstract.apply(lambda x: regex.sub(' ',x))

#Remove stop words
stops = set(stopwords.words("english")) #stops
stops = stops.union(['I'])

papers.loc[:,'title'] = papers['title'].apply(lambda x: x.split(' '))
papers.loc[:,'title'] = papers['title'].apply(lambda x: [word for word in x if
 word not in stops])

papers.loc[:,'abstract'] = papers['abstract'].apply(lambda x: x.split(' '))
papers.loc[:,'abstract'] = papers['abstract'].apply(lambda x: [word for word i
n x if word not in stops])

def build_corpus(data):
    "Creates a list of lists containing words from each sentence"
    corpus = []
    for col in ['title','abstract']:
        for sentence in data[col].iteritems():
            corpus.append(sentence[1])

    return corpus

corpus = build_corpus(papers)
```

In [4]:
```
model = word2vec.Word2Vec(corpus, size=200, window=10, min_count=500, workers=
4, seed=82)
model.corpus_count

def tsne_plot(model):
    "Creates and TSNE model and plots it"
    labels = []
    tokens = []

    for word in sorted(model.wv.vocab):
        tokens.append(model.wv[word])
        labels.append(word)

    tsne_model = TSNE(perplexity=50, n_components=2, init='pca', method='exac
t', n_iter=2500, random_state=23)
    new_values = tsne_model.fit_transform(tokens)

    x = []
    y = []
    for value in new_values:
        x.append(value[0])
        y.append(value[1])

    plt.figure(figsize=(16, 8))
    for i in range(len(x)):
        plt.scatter(x[i],y[i])
        plt.annotate(labels[i],
                     xy=(x[i], y[i]),
                     xytext=(5, 2),
                     textcoords='offset points',
                     ha='right',
                     va='bottom')
    plt.xlabel('TSNE Component1')
    plt.ylabel('TSNE Component2')
    plt.show()

tsne_plot(model)
```



3. NMF for topic modeling and t-SNE for 2D-embedding

We have used 2D-embeddings to visualize the content of all NIPS papers until 2017. In doing so, we have used the method in [1] as a benchmark.

We have choosen the topics for clusters from our WordCloud analysis and the tsne clusters in section 1 and section 2 above for the words with higher appearance in NIPS papers till 2017. These topics are:

neural network, bayesian, clustering, optimization, learning, kernel, artificial, reinforcement, image.

[1]. https://www.kaggle.com/rjhere23/nips-papers-visualized-with-nmf-and-t-sne (https://www.kaggle.com/rjhere23/nips-papers-visualized-with-nmf-and-t-sne)

In [5]:
```
#For this analysis we will use "Papers Text" to identify the growth of the top
ics from 1997 until 2017.
papers = pd.read_csv(path_to_csv)

n_features = 1000
n_topics = 9
n_top_words = 10


# GET TFIDF FOR THE TOP 1000 WORDS IN THE PAPER TEXT
tfidf_vectorizer = TfidfVectorizer(max_df=0.95, min_df=2,max_features=n_featur
es,stop_words='english')
tfidf = tfidf_vectorizer.fit_transform(papers['paper_text'])

nmf = NMF(n_components=n_topics, random_state=0,alpha=.1, l1_ratio=.5).fit(tfi
df)
tfidf_feature_names = tfidf_vectorizer.get_feature_names()
```

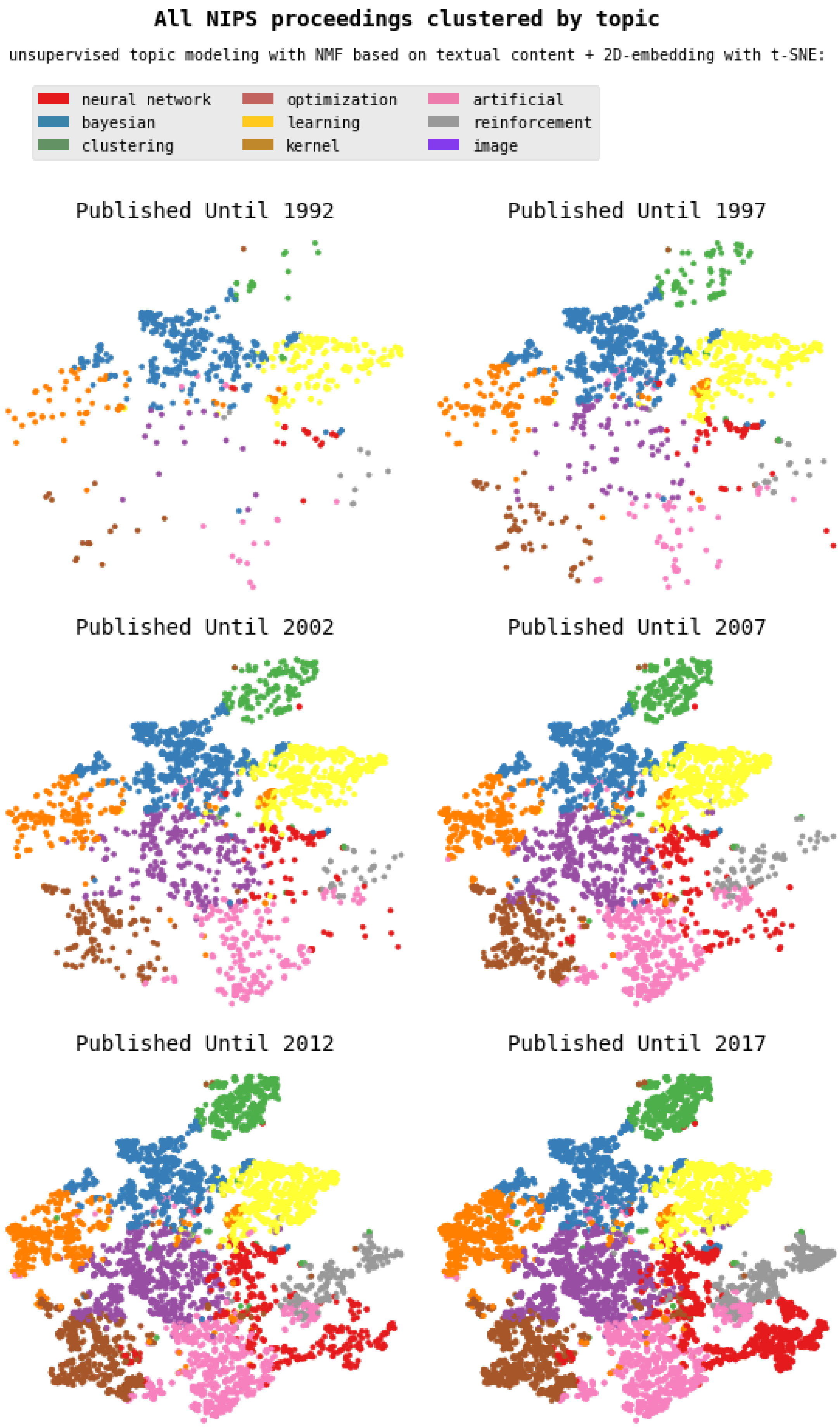
In [6]:
```
nmf_embedding = nmf.transform(tfidf)
nmf_embedding = (nmf_embedding - nmf_embedding.mean(axis=0))/nmf_embedding.std
(axis=0)
```

In [7]:
```
topics = ['neural network',
          'bayesian',
          'clustering',
          'optimization',
          'learning',
          'kernel',
          'artificial',
          'reinforcement',
          'image']
```

In [8]:
```
tsne = TSNE(random_state=3211)
tsne_embedding = tsne.fit_transform(nmf_embedding)
tsne_embedding = pd.DataFrame(tsne_embedding,columns=['x','y'])
tsne_embedding['hue'] = nmf_embedding.argmax(axis=1)
```

In [9]:
```
###code used to create the plot for getting the colors
#plt.style.use('ggplot')
colors = np.array([[ 0.89411765,  0.10196079,  0.10980392,  1. ],
                   [ 0.22685121,  0.51898501,  0.66574396,  1. ],
                   [ 0.38731259,  0.57588621,  0.39148022,  1. ],
                   [ 0.7655671 ,  0.38651289,  0.37099578,  1. ],
                   [ 1.        ,  0.78937332,  0.11607843,  1. ],
                   [ 0.75226453,  0.52958094,  0.16938101,  1. ],
                   [ 0.92752019,  0.48406   ,  0.67238756,  1. ],
                   [ 0.60000002,  0.60000002,  0.60000002,  1. ],
                   [ 0.51898501,  0.22685121,  0.92752019,  1. ]])

legend_list = []

for i in range(len(topics)):
    color = colors[i]
    legend_list.append(mpatches.Ellipse((0, 0), 1, 1, fc=color))
```

In [10]:
```
matplotlib.rc('font',family='monospace')
plt.style.use('ggplot')


fig, axs = plt.subplots(3,2, figsize=(10, 15), facecolor='w', edgecolor='k')
fig.subplots_adjust(hspace = .1, wspace=0)

axs = axs.ravel()

count = 0
legend = []
for year, idx in zip([1992,1997,2002,2007,2012,2017], range(6)):
    data = tsne_embedding[papers['year']<=year]
    scatter = axs[idx].scatter(data=data,x='x',y='y',s=10,c=data['hue'],cmap=
"Set1")
    axs[idx].set_title('Published Until {}'.format(year),**{'fontsize':'14'})
    axs[idx].axis('off')

plt.suptitle("All NIPS proceedings clustered by topic",**{'fontsize':'14','wei
ght':'bold'})
plt.figtext(.51,0.95,'unsupervised topic modeling with NMF based on textual co
ntent + 2D-embedding with t-SNE:', **{'fontsize':'10','weight':'light'}, ha='c
enter')
#fig.legend(legend_list)
fig.legend(legend_list,topics,loc=(0.1,0.89),ncol=3)
plt.subplots_adjust(top=0.85)

plt.show()
```


All NIPS proceedings clustered by topic
unsupervised topic modeling with NMF based on textual content + 2D-embedding with t-SNE:
neural network
bayesian
clustering
optimization
learning
kernel
artificial
reinforcement
image
Published Until 1992
Published Until 1997
Published Until 2002
Published Until 2007
Published Until 2012
Published Until 2017

The tsne plots above gives us a good indication of the growth of each area over several year blocks.
We will go on to apply some other techniques to try to find the exact trends computationally. One disadvantage for assigning topics is that the topic names that are assigned is somewhat subjective and does not give us a definative answer to relative growth of one topic vs another.

4. Find top topics using LDA and plot them against time

Since topic modeling is somewhat subjective, we also used LDA to try to model topics and see if we can find trends. To do this, we first found 9 topics and looked at the words with the highest probabilities. We also looked at the articles that have the highest probability to be assigned to each topic and used that to define the topic names.
Then we took all the papers from each year and took the mean of their probabilities for each topic. We plotted the topics against time (in years) to see if there is any visible trend.

In [11]:
```
df_papers = pd.read_csv(path_to_csv)
df_papers_orig = df_papers.copy()

# LOWER CASE
df_papers.loc[:,'title'] = df_papers.title.apply(lambda x : x.lower())
df_papers.loc[:,'paper_text'] = df_papers.paper_text.apply(lambda x : x.lower
())

#KEEP ONLY ALPHANUMERIC
regex = re.compile(r'\W+')
df_papers.loc[:,'title'] = df_papers.title.apply(lambda x: regex.sub(' ', x))
df_papers.loc[:,'paper_text'] = df_papers.paper_text.apply(lambda x: regex.sub
(' ', x))

#CONVERT TO BOW
df_papers.loc[:,'title'] = df_papers['title'].apply(lambda x: x.split(' '))
df_papers.loc[:,'paper_text'] = df_papers['paper_text'].apply(lambda x: x.spli
t(' '))

stops = set(stopwords.words("english"))
stops = stops.union(set("year"))

#REMOVE STOP WORDS
df_papers.loc[:,'title'] = df_papers['title'].apply(lambda x: [word for word i
n x if word not in stops])
df_papers.loc[:,'paper_text'] = df_papers['paper_text'].apply(lambda x: [word
for word in x if word not in stops])

# INCREASE WEIGHT ON THE WORDS USED IN THE TITLES BY COUNTING THEM 4 times
title_overcount_factor = 3

def build_corpus(data):
    corpus = []
    for index, row in data.iterrows():
        title = []
        for i in range(title_overcount_factor):
            title = row['title'] + title
        content = title + row['paper_text']
        corpus.append(" ".join(content))
    return corpus

corpus = build_corpus(df_papers)
```

In [12]:
```
# SOME PARAMETERS USED LATER
n_samples = len(corpus)
n_features = 2000
n_top_words = 20

tf_vectorizer = CountVectorizer(max_df=0.95, min_df=2,
                                max_features=n_features)
t0 = time()
tf = tf_vectorizer.fit_transform(corpus)
print("done in %0.3fs." % (time() - t0))
```

```
done in 15.463s.
```

In [13]:
```
n_components = 9
n_top_words = 20

print("Fitting LDA models with tf features, "
      "n_samples=%d and n_features=%d..."
      % (n_samples, n_features))
lda = LatentDirichletAllocation(n_components=n_components, max_iter=5,
                                learning_method='online',
                                learning_offset=50.,
                                random_state=0)
t0 = time()
lda.fit(tf)
print("done in %0.3fs." % (time() - t0))
```

```
Fitting LDA models with tf features, n_samples=7241 and n_features=2000...
done in 97.775s.
```

In [14]:
```
def print_top_words(model, feature_names, n_top_words):
    for topic_idx, topic in enumerate(model.components_):
        message = "Topic #%d: " % topic_idx
        message += " ".join([feature_names[i]
                             for i in topic.argsort()[:-n_top_words - 1:-1]])
        print(message)
        print()
    print()


print("\nTopics in LDA model:")
tf_feature_names = tf_vectorizer.get_feature_names()
print_top_words(lda, tf_feature_names, n_top_words)
```

```
Topics in LDA model:
Topic #0: learning kernel data loss xi classification function problem traini
ng regression class algorithm methods error method linear yi label convex bas
ed

Topic #1: learning state policy action time algorithm value function reward r
egret optimal agent problem states actions reinforcement control decision bas
ed model

Topic #2: model time neurons neural figure neuron input spike system activity
response information stimulus fig network signal cells cell noise brain

Topic #3: algorithm algorithms graph problem gradient optimization time tree
learning node xt function convex nodes number convergence stochastic online p
roblems step

Topic #4: matrix data clustering sparse algorithm rank problem points matrice
s method analysis dimensional cluster low number methods spectral linear clus
ters figure

Topic #5: theorem log function bound distribution probability let case bounds
random functions sample given information error theory proof following lemma
consider

Topic #6: network networks neural learning training input layer output deep h
idden units weights error trained performance figure number data layers weigh
t

Topic #7: model data models distribution inference gaussian bayesian log like
lihood parameters posterior latent variables prior process variational sampli
ng number given probability

Topic #8: image model images features object feature recognition figure based
objects learning models different training visual human use information word
dataset
```

In [15]:
```
doc_topic_distrib = lda.transform(tf)
print(doc_topic_distrib.shape)

top_n_titles = 5
for i in range(n_components):
    idx=doc_topic_distrib[:,i].argsort()[::-1][:top_n_titles]
    doc_topic_distrib[idx]
    print("Topic %d" %i )
    print(df_papers_orig.loc[idx,'title'].values)
    print()
```

```
(7241, 9)
Topic 0
['A General and Efficient Multiple Kernel Learning Algorithm'
 'Similarity-based Learning via Data Driven Embeddings'
 'Learning with Average Top-k Loss'
 'Efficient Convex Relaxation for Transductive Support Vector Machine'
 'Learning Kernels with Radiuses of Minimum Enclosing Balls']

Topic 1
['Learning to Take Concurrent Actions'
 'The Effect of Eligibility Traces on Finding Optimal Memoryless Policies in
Partially Observable Markov Decision Processes'
 'Improved Switching among Temporally Abstract Actions'
 'Cyclic Equilibria in Markov Games'
 'Playing is believing: The role of beliefs in multi-agent learning']

Topic 2
['An Analog VLSI Model of Periodicity Extraction'
 'Neuronal Maps for Sensory-Motor Control in the Barn Owl'
 'Stimulus Encoding by Multidimensional Receptive Fields in Single Cells and
Cell Populations in V1 of Awake Monkey'
 'Computer Simulation of Oscillatory Behavior in Cerebral Cortical Networks'
 'A model of transparent motion and non-transparent motion aftereffects']

Topic 3
['Minimum Weight Perfect Matching via Blossom Belief Propagation'
 'Linear Convergence with Condition Number Independent Access of Full Gradien
ts'
 'Linear programming analysis of loopy belief propagation for weighted matchi
ng'
 'Decomposable Submodular Function Minimization: Discrete and Continuous'
 'Online Sum-Product Computation Over Trees']

Topic 4
['High-Rank Matrix Completion and Clustering under Self-Expressive Models'
 'Sparse Manifold Clustering and Embedding'
 'SpaRCS: Recovering low-rank and sparse matrices from compressive measuremen
ts'
 'Self-Tuning Spectral Clustering'
 'Scalable Methods for Nonnegative Matrix Factorizations of Near-separable Ta
ll-and-skinny Matrices']

Topic 5
['Polynomial Uniform Convergence of Relative Frequencies to Probabilities'
 'Submultiplicative Glivenko-Cantelli and Uniform Convergence of Revenues'
 'On the Reliability of Clustering Stability in the Large Sample Regime'
 'Rademacher Complexity Bounds for Non-I.I.D. Processes'
 'PAC-Bayesian Generic Chaining']

Topic 6
['Consonant Recognition by Modular Construction of Large Phonemic Time-Delay
Neural Networks'
 'A B-P ANN Commodity Trader'
 'The Recurrent Cascade-Correlation Architecture'
 'Information Measure Based Skeletonisation'
 'Skeletonization: A Technique for Trimming the Fat from a Network via Releva
nce Assessment']
```

```
Topic 7
['The Infinite Gaussian Mixture Model' 'Rethinking LDA: Why Priors Matter'
 'Latent Dirichlet Allocation' 'Collapsed Variational Inference for HDP'
 'Dependent Multinomial Models Made Easy: Stick-Breaking with the Polya-gamma
Augmentation']

Topic 8
['Im2Text: Describing Images Using 1 Million Captioned Photographs'
 'Cascaded Classification Models: Combining Models for Holistic Scene Underst
anding'
 '3D Object Detection and Viewpoint Estimation with a Deformable 3D Cuboid Mo
del'
 'Learning about Canonical Views from Internet Image Collections'
 'Memorability of Image Regions']
```

In [16]:

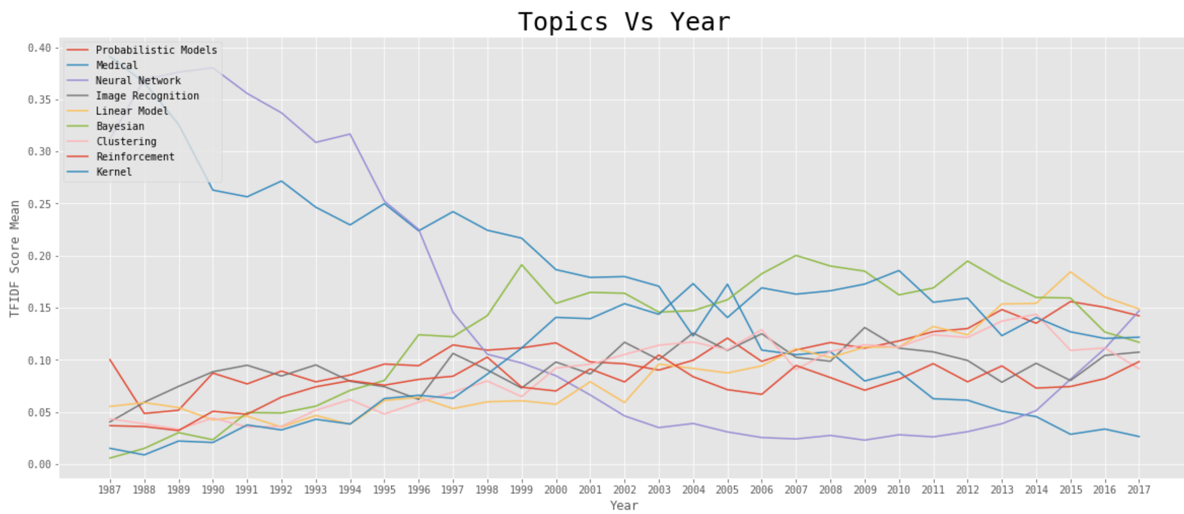
```
# BASED ON THE ARTICLES FOR EACH TOPIC THE TOPIC NAMES ARE ASSIGNED AS FOLLOWS
topic_names = {0:'Kernel',
               1:'Reinforcement',
               2:'Medical',
               3:'Linear Model',
               4:'Clustering',
               5:'Probabilistic Models',
               6:'Neural Network',
               7:'Bayesian',
               8:'Image Recognition',
              }
```

In [17]:

```
topic_list = [value for key, value in topic_names.items()]
df_topics = pd.DataFrame(doc_topic_distrib, columns=topic_list)
print(df_topics.shape)
df_topics.head()
df_topics['year'] = df_papers['year']
```

```
(7241, 9)
```

In [23]:
```
df_topics_year = df_topics.groupby('year').mean()
topics = set(topic_list)

def plot_trend(df, topics, title):
    plt.figure(figsize=(20,8))
    plt.title(title, fontsize=25)
    for topic in topics:
        plt.plot(df.index, df.loc[:,topic])
    plt.xticks(df.index)
    plt.legend(loc = 'upper left')
    plt.xlabel("Year")
    plt.ylabel("TFIDF Score Mean")

plot_trend(df_topics_year, topics, "Topics Vs Year")
```



Looking at the above plot it is easy to spot a few upward and downward trends.
For example, we can clearly see that neural network was mentioned highly in the early nineties but it declined after that.
It is showing a positive trend again in recent years.
However, we are less confident in the trends depicted by the other topics because of two reasons:
a. We cannot conclusively assign a name to the topics because the words they represent are somewhat ambigious.
b. If the algorithm did not manage to seperate different topics accurately, it might be averaging the trends of different domains
giving us incorrect trends.

5. Use TFIDF to find the important terms for each year and find the UPWARD and DOWNWARD trending terms. (FINAL APPROACH)

After looking at the trends based on topics, we realised that it was fairly difficult to assign topics to the clusters of words and the process is highly subjective.

We decided to pursue a different path and use raw tfidf scores on two word terms. Two word terms seemed to represent larger ideas and concepts fairly well. And because we have a large number of papers and text for each year, we were able to plot the upward trending concepts and downward trending concepts using the tfidf scores for the relevant two word terms.

After the initial plot, we recognized several terms that are not relevant to machine learning and we created a list to filter those out.

In [21]:

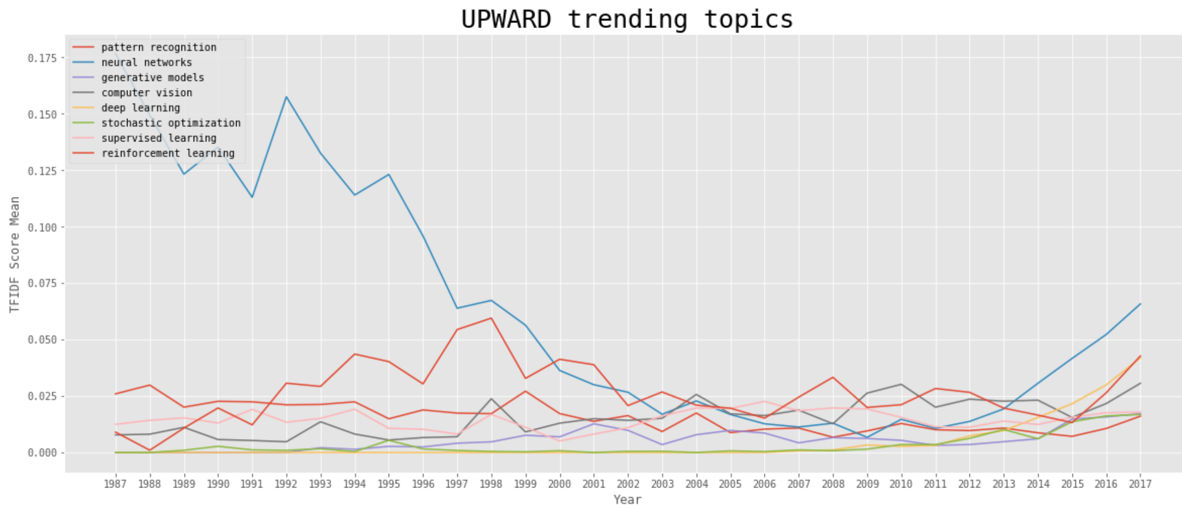
```
# PARAMETERS FOR TFIDF
min_ngram = 2
max_ngram = 2

max_df = 0.90
min_df = 2
max_features = 500

vectorizer = TfidfVectorizer(ngram_range=(min_ngram, max_ngram), max_features
= max_features, max_df = max_df)
X = vectorizer.fit_transform(corpus)
print(X.get_shape())

# CONVERT TFIDF RESULTS TO PANDAS DATA FRAME
df_tfidf = pd.DataFrame(X.toarray(), columns=vectorizer.get_feature_names())

# ADD THE YEAR COLUMN TO THE DATAFRAME
df_tfidf['year'] = df_papers['year']
df_tfidf['count'] = 1

#GET THE NUMBER OF PAPERS FOR EACH YEAR
counts = df_tfidf.groupby(['year']).agg(['count'])['count']

#TAKE THE MEAN IDF SCORE FOR EACH FEATURE
df_tfidf_year = df_tfidf.groupby(['year']).mean()

#ADD THE COUNT COLUMN FOR EACH YEAR FOR FUTURE USE
df_tfidf_year['count'] = counts
```

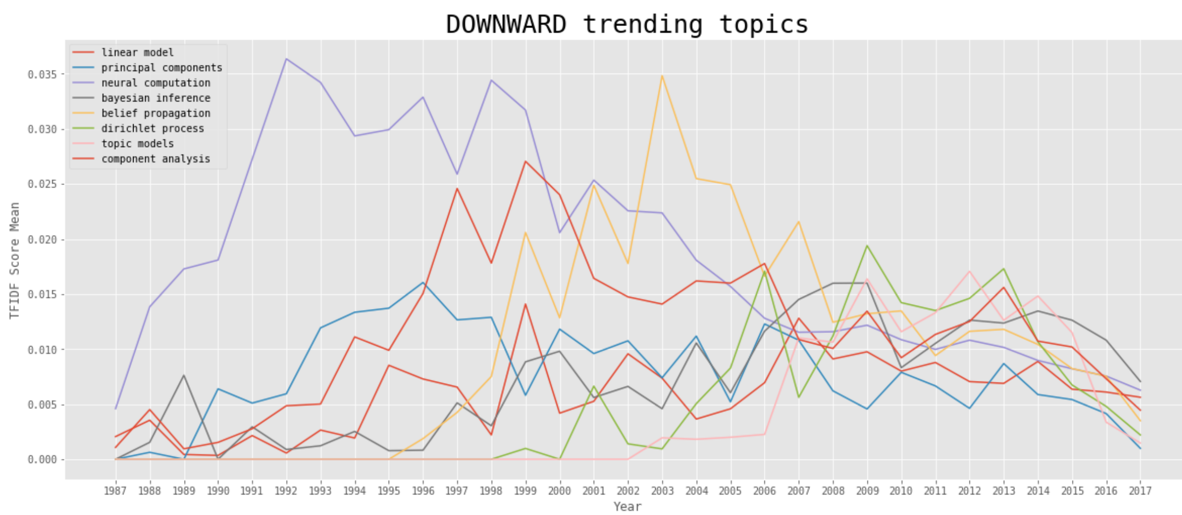
```
(7241, 500)
```

In [24]:
```
# PLOT ONLY TERMS THAT HAVE A CONSISTENTLY RISING TREND
plt.rcParams['figure.figsize'] = [10, 5]
def upward_trend (column):
        upward_trend = df_tfidf_year.loc[2017,column] > df_tfidf_year.loc[2016
, column] > df_tfidf_year.loc[2015, column]
        return upward_trend

def downward_trend(column):
        downward_trend = df_tfidf_year.loc[2017,column] < df_tfidf_year.loc[20
16, column] < df_tfidf_year.loc[2015, column]< \
        df_tfidf_year.loc[2014, column]
        return downward_trend


topics_upward = set()
topics_downward = set()
for column in df_tfidf_year.columns:
    if upward_trend(column) :
            topics_upward.add(column)
    elif downward_trend(column):
            topics_downward.add(column)



# REMOVE TOPICS THAT ARE KNOWN TO BE NOT RELATED TO MACHINE LEARNING OR HAVE A
NOTHER SIMILAR REPEATED TERM
remove_set = set(["systems pages", "neural network", "related work", "conferen
ce neural", "mini batch"
                   "log log", "low rank", "end end", "international conferenc
e", "arxiv preprint",
                  "related work", "preprint arxiv", "two different", "long ter
m" , "fixed point", "error rates", "standard deviation",
                  'et al', 'kernel methods',  'supported part', 'multi task',
'total number',
                  'two dimensional', 'cifar 10', 'natural language', 'error ra
tes', 'task learning', 'artificial neural', 'editors advances',
                  'standard deviation', 'count', 'pattern analysis', 'optimal
 policy', 'reward function',
                  'deep neural', 'number iterations', 'analysis machine', 'ker
nel function', 'recurrent neural', 'state action', 'gaussian kernel',
                  'joint distribution', 'function approximation', 'input spac
e', 'international conference', 'number parameters', 'proceedings ieee',
                  'proposed method', 'real data', 'information processing', 'd
omain adaptation',
                  'conference computer', 'learning methods', 'model based', 'x
0 x0', 'processing systems', 'end end', 'advances neural',
                  'neural network', 'density estimation', 'al 2016', 'conferen
ce neural', 'theoretical analysis', 'see figure',
                  'ground truth', 'linear combination', 'state art', 'syntheti
c data', 'theoretical results', 'cost function', 'see fig', 'recent work',
                  'arxiv preprint', 'high probability', 'results shown', 'expe
rimental results', 'systems pages', 'labeled data',
                  'training data', 'two different', 'mini batch', 'preprint ar
xiv', 'would like', 'neural information', 'conference learning',
                  'mean squared', 'prior knowledge', 'machine intelligence','s
ystem nips', '40 50', 'fixed point', 'non gaussian', 'long term', 'non paramet
```

```
ric', 'information theoretic', 'related work'
                  'neural computation', 'ij ij', 'gaussian noise', '20 30', 'p
rincipal component', '15 20', 'given set', 'xi xj', '13 14', 'mixture model',
'vector machine', 'small number', 'message passing',
                  'high dimensional', 'covariance matrix', 'nips pages', 'desc
ribed section', 'firing rate', 'mit press', 'previous work', 'diagonal matrix'
, '16 17',
                  'em algorithm', 'learning rule', 'markov random', 'data poin
ts', 'technical report', '100 150', '20 40', 'least squares', 'many applicatio
ns', 'fig shows', 'graphical model',
                  'learning problems', 'edu abstract', 'gaussian mixture', '40
 60', 'number clusters', '20 10', 'one dimensional', 'random fields',
                  'feature selection', 'state space', 'sample size', 'non zer
o', 'graphical models', 'science university', 'partition function', 'xt xt',
                  'main result', 'special case', 'systems nips', 'vision patte
rn', 'signal processing', 'network architecture','dynamic programming', 'kerne
l matrix',
                  'markov decision', 'kernel learning', 'maximum likelihood',
'computational cost', 'computational complexity', 'likelihood function'

                 ])

# FINAL LIST OF TOPICS TO PLOT
topics_upward = topics_upward.difference(remove_set)
topics_downward = topics_downward.difference(remove_set)

#topics = set(["computer vision", "deep learning", "neural networks", "value f
unction", "pattern recognition",
#                "reinforcement learning" ,"information processing"])




plot_trend(df_tfidf_year, topics_upward, "UPWARD trending topics")
plot_trend(df_tfidf_year, topics_downward,  "DOWNWARD trending topics")

print("UPWARD:")
print(topics_upward)
print("DOWNWARD:")
print(topics_downward)
```

```
UPWARD:
{'pattern recognition', 'neural networks', 'generative models', 'computer vis
ion', 'deep learning', 'stochastic optimization', 'supervised learning', 'rei
nforcement learning'}
DOWNWARD:
{'linear model', 'principal components', 'neural computation', 'bayesian infe
rence', 'belief propagation', 'dirichlet process', 'topic models', 'component
analysis'}
```





Conclusion

We conclude that the following fields have an UPWARD Trend in the recent years:

1. neural networks
2. deep learning
3. reinforcement learning
4. computer vision
5. generative models
6. pattern recognition
7. stochastic optimization
8. supervised learning

We can also conclude that the following areas have a DOWNWARD Trend in recent years:

1. principal components
2. linear models
3. dirichlet process
4. topic models
5. belief propagation
6. bayesian inference
7. neural computation
8. component analysis

We used several methods such as clustering and LDA to try to understand trends within subfields and topic catagories.
In the end, because of the subjective nature of the topic allocation methods, we used TFIDF scores to computationally detect trends and believe the above observations are more accurate and does not rely on the ambiguity of topic allocation.