Phoneme/Text

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Idea:

Train to HMMs using the CMU dataset.

One for word to phoneme conversion and the other for phoneme to word.

As the CMU dataset is tagged, this becomes a supervised learning problem.

We use the MLE to find HMM parameters and Viterbi to do the actual conversion.

Idea: (Contd.)

The transitions are of the form

S I $\Rightarrow|$ O $|\Rightarrow$ S II

Where O is the observation and S I and S II are the hidden states.

We have pruned the data set so that only words where the number of graphenes are equal to the number of phonemes are considered.

Idea: (Contd.)

For grapheme to phoneme conversion the states are the phoneme and graphemes are the observations.

The opposite is done when converting phonemes to graphemes.

Idea: (Contd.)

$P(S\ I \Rightarrow |\ O\ | \Rightarrow S\ II) = n(S\ I \Rightarrow |\ O\ | \Rightarrow S\ II)/n(S\ I)$

n(S I) = no of times S I appears in the data set.

n(S I $\Rightarrow$ | O | $\Rightarrow$ S II) = number of times S I is followed by SII in the dataset with O in the observation sequence corresponding to S II.

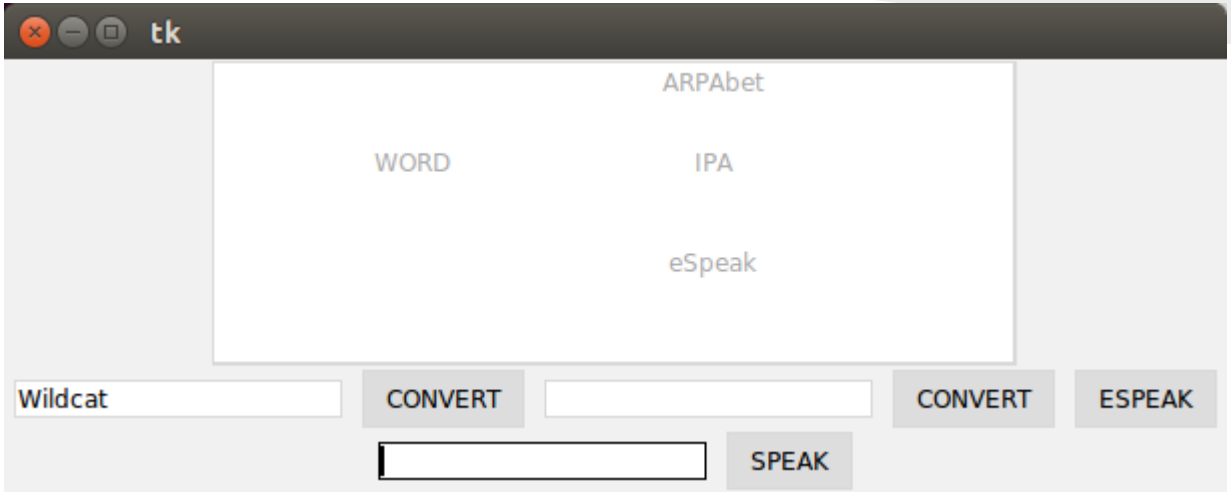
Implementation

We store a transition table to store the probabilities which we store in a file to avoid repeated training.

The phoneme sequence is made using the ARPABET notation. To produce sound we convert the output in ARPABET to ESpeak notation (IPA).

There is a GUI interface to do the conversion

Interface



UI interface and API to allow for easier usage

Interface Properties

Allows for word to phoneme and phoneme to word conversion.

Word can be converted to IPA, ARPAbet or eSpeak notation.

The user can also simply enter a sentence which he or she wants to speak and it will speak it.

Performance:

We performed 5 fold cross validation after permuting the input set. The results are as follows:

Average Word Conversion Accuracy : 0.7338947118582697

Average Phoneme Conversion Accuracy : 0.8014263311120567

Confusion Matrix (GrGr)

	@	A	'	S	.	B	E	R	G	C	H	N	K	L	I	Y	T	M	O	D	V	U	W	Z	F	X	J	Q	-	P	_
@																															
A	4			81		20	1689		83	16	105		10	57	34	329		492		9	77	44	2448		16	14	271		26	2	14	7				25		
'		19		17	1		61	2				25		12	18	2	7	11	12	4	1			1	4	3				2		
S	4	76	3					70	2	1	643		1	26	2	15	40	2	34	1	62		1	39		425		4	3			4	1	
.		1		3			7	2		2		2		3	12	1	1	3				1		1	1	1						
B	3	25		15			1	3						3	14		1	18	9			19										
E	4	2505		138		139			29		91	27	80	4	163		16	664		3079		313		266		58	688		54	64	156		6	22	13	34	17			51		
R	3	42		3		15	209			3	19	1	9	8	5	67	2	70	7	72	6	4	10	2		4	1	1			22										
G	2	8		2			18	1		4	3	246		4		8				28	1		6				5	125												
C	3	91	3	1069				193		245		2		1	24	1512		3	100		13	101		1	9			23		21		104			14		17				
H		29		7			12	6	2	32		4	4	7	18	8	19	1	15			18	13		7	1	3		6											
N	2	192			1			91	6	3				3		334		16	8	1	45	5		61									5							
K	3	18		16			3	93		2022		1	5		2	3	1			4			6				31		13											
L	2	557			30		6	143		4	4	48	1		5		82	3	8		135			123			1					42							
I	4	769		1	155			12	1969		71	8	85	11	119		27	162			841		291		48	303		39	17	87	5	85	15	7	21			40		
Y	1	31		5		2	239		4		16	1	6		8	2479			12	1	27	4	1	57	2		3		164				1						
T	1	288			135				56	18		167		3	41	1	6	68				30	8		9		32	2	1				1	1					
M	3	90		44		3	17	8						8	14					17			45			1													
O	8	4139			30		7	288		51	9	18	10	22	21	77	156		3	45	17		24	6	109		26		6	21	1			24					
D		37				1	34	7	27	1		27		9	22	6	31		11			17				8													
V	2	16					7	3				1		6	59		3		12	1		2	11		17													
U	1	1672			64		2	375		23	6	21	11	26	5	90	312		163		16	13	392		5			209		2	2	6	21	1		4			
W		10		33			1	4		1	3	1		9	6		4		11		66	48			19			4											
Z	2	4		1100			1	3			2	2			1	30	2	86		1			1																
F		33		1			14	5				2		5	15				4		5	4	76						3										
X	3			90			4	1	57	169				132			1		11					2		22					7								
J	1	3		9			1		266		6	23	1			16	60	1	1	5	2		30	3															
Q				2			1	1		97			137			1				1																			
-		3		1				1			2	2	1	1	5	1	2					2				2					2								
P	1	22		119				5	6						12	2	1	3	7	7			1	1		16													
_				1								7			1														1										

Confusion Matrix (GrGr) conclusions

We can see that some alphabets are characteristic of being confused to others

A↔E,A↔O,S↔C, E↔I etc.

These confusion are legitimate as even english has these issues.

Confusion Matrix(PhPh)

	@	AA	AE	AH	AO	AW	AY	B	CH	D	DH	EH	ER	EY	F	G	HH	IH	IY	JH	K	L	M	N	NG	OW	OY	P	R	S	SH	T	TH	UH	UW	V	W	Y	Z	ZH
@																																									
AA			1045	2352	32	2	1	13		6		452			144		4		4	10	9	1	10	10	1	15		1828		4	15	3		10			15	1	5	2	2
AE		1343		2698	13			2		3		157			93	4		7	3	8		24	9	16	42	1	3		6	7	7		11	4		3	4	3	3	3		
AH		1818		1573		25		16	18		31			2191		12	261		19	18	15	1326		573		3	69	1238		49	141		2	1989			16	23	47		86		12	447
19	32	259		126																																				
AO		896		81	168					2				5	1		1			6			1			7	6	1		5	378			2	30			4		3	2				1		
AW		8		11											2																15				1			5							
AY		7	1	96				1		11		9	5	7				672		676		1	2	11	1	22			1		10	8	1	36			4		4	12	25		
B	1	12	1	16	1					1		22		1				8	6			4	3			3			15	2					7				1			
CH	1			6													3		5		186		1					1		79		79			6			1	1			
D		9		47	6		3					6		2				33	23		8	4		8		10			6			9			21	1		1				
DH																																									
EH	1	434		3	1233		1			2	4	4			1	7	2		4	710		301			24	65	14	58			1	32	68		20	1	14	33	4		32	19		
ER		22	1	10	7							69						5		1								504						9	12		2					
EY	3	342		428		672				2			2		368				1		3	63	89		17	26	5	17		1		1	1	11		315			3	1	1	16	4	
F		7	2	15	13		3					5					8	8	10		9	8	1	2		3		15	4	3		2			10	20		4				
G		6		14	1							2		1				10		177		66	5		12	19	3			2					8		4		3			
HH		1	6	2			1					2		1		3		5		19	7			1		6			1	2							4	9	5			
IH	2	8	5	1231				210		1	4	21			1701		32	5	5	5	8		2287		3	30	96	10	54	220		10		3	34	58		68	1		28	56	6	21	16	
IY	7	4	2	942			2	182		1		4			806		27	34	1	1	1	1581			2	7	56	4	22		1			18	23	19	36			5	1	2	86	11		
JH	1	3		3						35		6					489			16	4			1		2		4		1			41			3			35	3			
K	1	80	34	46	6			18		25		56			19	18	11	41	17			72	32	39	3	3		8	24	385			27		1	27	5	9	4	6			
L		58	13	363		3		1	2		10		937			1	37	1		7	117		26		4		1	8		13		12	22			56			26	6	6	7	4		
M	1	17	3	48			8	8				57	1					36	6		6			4		5		7	8	1				1	9			5					
N		7	4	129				1		2	34		43	1	2		18	2	56	77	2	6	3			255		17			12	44		46			26	1	2	13	3			
NG			1														221		4		3	6			112						2					11						
OW		618		2	846		46			1		8			2		1	1	1		2		5	10	1	11				8	19	7		21			2	3	7	2	7			
OY				2														1	6			5				2					2					1	6					
P	3	14	16	16	3							39	3	2	3			14	5		3	40				4			15	4		6			13							
R		21	30	73	3	1						29	179		4	2	1	2	45	47		4	8	1	4		16		3		2		38		5	27		1		1			
S	1	22	4	53	9		1	10	1	1		79	1	3	5	5	10	71	73		819		15	4	10		13		7	12			115			103			9	32	991		33	
SH				2								2					13	3	190			21	2		1		2				22		35					8				
T	1	32	5	41	44		8	3		32		141		3	42	1		2	162		93	2	9	20		10		7		2	69	8			1		32	3		2	17			
TH			6	1					1							5														1		15			1						
UH		3		40	1							7	2					18	1		3			2		14			76	3				109			52	1			
UW	1	9		1070		2	1		30		30		32	1		18	22	4	19	4	8	32	128		64	77		30		6	22	69		114		17			58	76	39		
V		7	2	17	1		1					48	1	2	12		6	8	12			4		1		4			4	1		1				52	1					
W		12		26	1		4	1				8		2	16		82	5	3		9	10	1			13			7	4		2		1	39	3		73	1			
Y	1	4	1	693				11	26		2		22			2	3	18	6	342		163		27	10	7	20		9	2	1	4	26	5	26		98	113			42		4		
Z	5	21	8	25			1					58	2				3	156		17		3	2		5		1			1	2953		2	14		23			2		3		
ZH				1													8	1		8	7		3								7	5	1		2	2			5	8			

Confusion Matrix (PhPh)

conclusions

We can see that some phonemes are characteristic of being confused to others

AA↔AE,AA↔AH,OW↔AA, AH↔AE etc.

These confusion are legitimate as the sounds are close and their occurrences are in generally similar surrounding context.

Optimisation Attempts

1) Non Zero probability initially
2) Trigram Model
3) Neural Networks(Later)

Non Zero initial probability

The logic behind this is that many possibilities of the state diagram is nullified by the 0 probabilities existing due to no data seen for these transitions.

Instead of 0 we add 10-10 to allow for some weightage. We see not too much improvement of 0.01%(not much huh!)

Average Word Conversion Accuracy : 0.7430759192440042

Average Phoneme Conversion Accuracy : 0.8014293446848637

Trigram:

We changed the state machine to work with trigrams. The results were as follows:

Average Word Conversion Accuracy : 0.6153025931351043

Average Phoneme Conversion Accuracy : 0.7398425392381858

Trigram Output Analysing

The performance of the machine reduces with the trigram assumption(besides it takes significantly more time to solve), this is expected for the reason that the new state transistion ((S1,S2),S3,O) requires more training to get trainined and that the english model for equi-phone-grapheme words may not be too much effected by this assumption.

Thank You