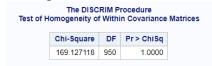
## Linear Discriminant Analysis:

In order to predict/classify Foundation Type, We would build a LDA model using the training data set. Since LDA does not support inclusion of categorical variables in the model, We will analyze continuous variables as independent variables for this model.

#### **Assumptions:**

- Normality criteria for LDA has been taken care in our earlier proc **glmselect** model. We have transformed the required variables which we continue to use.
- Homogenous variance-covariance:



Since the Chi-Square test fails for homogenous variance, we will address this by using pool covariance.

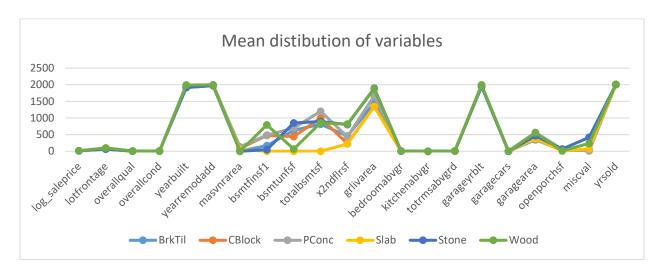
#### **Analysis:**

In our model, we start off by looking at difference in mean value for each independent variable against foundation factor. Table of mean and frequency across foundation type.

Variable	BrkTil	CBlock	PConc	Slab	Stone	Wood
Frequency	146	634	647	24	6	3
	Mean	Mean	Mean	Mean	Mean	Mean
log_saleprice	11.7225277	11.8700797	12.2616651	11.5329593	11.9331562	12.1024793
lotfrontage	61.4394358	70.1638853	70.994341	66.1343133	66.6666667	102.2149013
overallqual	5.4452055	5.4211356	6.9799073	4.2916667	5.6666667	6.6666667
overallcond	6.1986301	5.829653	5.202473	4.75	7	5.6666667
yearbuilt	1921.02	1961.25	1993.31	1959.58	1912.67	1990.33
yearremodadd	1971.62	1975.22	1998.05	1965.17	1978.33	1997
masvnrarea	7	86.4600188	133.6680639	51.4583333	0	0
bsmtfinsf1	165.8424658	477.1246057	484.0032077	0	45.8333333	791.6666667
bsmtunfsf	629.0479452	443.4716088	695.3292117	0	849.1666667	65.3333333
totalbsmtsf	814.6232877	1001.49	1200.88	0	895	857
x2ndflrsf	455.0068493	228.714511	436.8809892	218.8333333	800.8333333	818
grlivarea	1452.08	1355.5	1667.63	1339.46	1894.67	1876
bedroomabvgr	2.9178082	2.8609825	2.8438949	2.9166667	3.5	3
kitchenabvgr	1.0619494	1.05843	1.0093425	1.4583333	1.3333333	1
totrmsabvgrd	6.5547945	6.1340694	6.8686244	6.5	8.1666667	7
garageyrblt	1951.18	1967.66	1995.86	1969.08	1950.5	1990.33
garagecars	1.3082192	1.4952681	2.1468315	1.5	1.6666667	2
garagearea	344.6575342	410.8533123	566.1483771	375.0416667	464.3333333	555
openporchsf	26.9133409	32.4453435	63.0543646	8.7083333	67.8333333	14
miscval	27.5342466	33.5073863	9.3972179	71.868394	416.6666667	233.3333333

Yrsold   2007.73   2007.87   2007.77   2008.04   2008.67   200	Yrsold	Yrsc
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Lets, Plot the above mean distribution.



We can note that number of Cblock and PConc is very high and consumes 88% of the dataset. While slab and wood have negligible amount of data. This might cause misclassifying slab or wood type.

Variables masvnarea, bsmtfinsf1, bsmtunfsf, totalbsmtsf and x2ndflrsf differ noticeably between each foundation type. These predictor will have higher impact of classifying on foundation type to another.

Since chi-square test for within covariance failed, we will use pooled covariance in our model.

#### **Model building:**

We have run variaous models, thrown away variables with pvalue > 0.05. The below summary is of our final model.

#### Statistics:

				Pooled Covaria	nce Matrix Information
Total Sample Size	1460	DF Total	1459	Covariance	Natural Log of the Determinant of the
Variables	12	DF Within Classes	1454	Matrix Rank	Covariance Matrix
Classes	6	DF Between Classes	5	19	79.03045

Multivar	iate Statistics	and F App	oroximation	1S								
S=5 M=6.5 N=717												
Statistic	Value	F Value	Num DF	Den DF	Pr > F							
Wilks' Lambda	0.17625037	31.55	95	6992.1	<.0001							
Pillai's Trace	1.26646257	25.71	95	7200	<.0001							
Hotelling-Lawley Trace	2.56341658	38.71	95	5549	<.0001							
Roy's Greatest Root	1.65300566	125.28	19	1440	<.0001							
NOTE: F Statisti	c for Roy's Gr	eatest Roo	ot is an upp	er bound.								

Since the mean values of each response variable differ from the factor levels we move on to univariate analysis.

### **Frequency and Priors**

		Class Level	Informatio	n	
foundation	Variable Name	Frequency	Weight	Proportion	Prior Probability
BrkTil	BrkTil	146	146.0000	0.100000	0.422535
CBlock	CBlock	634	634.0000	0.434247	0.140845
PConc	PConc	647	647.0000	0.443151	0.415962
Slab	Slab	24	24.0000	0.016438	0.015023
Stone	Stone	6	6.0000	0.004110	0.003756
Wood	Wood	3	3.0000	0.002055	0.001878

From the information we can see that priors are arbitrary. The decision to set is based on frequency and probability of them happening, good accuracy model.

PConc has a prior of 0.42 because of its domination on the dataset. Although CBlock is frequent it has been reduced and BrkTile has been increased to reduce the misclassifications of BrkTile into CBlock.

Slab, Stone and wood have been kept low because of its frequency and probability of happening.

### **Comparing Mahalanobis distance within foundation types**

	Sq	uared Dista	nce to foun	dation			Prob > Mahalanobis Distance for Squared Distance to foundation								
From foundation	BrkTil	CBlock	PConc	Slab	Stone	Wood	From foundation	BrkTil	CBlock	PConc	Slab	Stone	Wood		
BrkTil	0	6.64709	14.33441	32.45816	4.95205	29.90824	BrkTil	1.0000	<.0001	<.0001	<.0001	0.0819	<.0001		
CBlock	6.64709	0	5.52319	24.34768	13.74802	18.33124	CBlock	<.0001	1.0000	<.0001	<.0001	<.0001	<.0001		
PConc	14.33441	5.52319	0	31.72738	22.02268	16.20705	PConc	<.0001	<.0001	1.0000	<.0001	<.0001	0.0003		
Slab	32.45816	24.34768	31.72738	0	34.04687	39.00079	Slab	<.0001	<.0001	<.0001	1.0000	<.0001	<.0001		
Stone	4.95205	13.74802	22.02268	34.04687	0	36.27761	Stone	0.0819	<.0001	<.0001	<.0001	1.0000	<.0001		
Wood	29.90824	18.33124	16.20705	39.00079	36.27761	0	Wood	<.0001	<.0001	0.0003	<.0001	<.0001	1.0000		

From the figure above we can note that the distances between Stone and BrkTil disnce is low, We can see that these fail the <u>Mahalanobis</u> significance test. classification for these cannot be justified.

Among all the types Slab, Stone and wood are reasonably different from each other and easier to classify.

## **Univariate analysis**

		Univa	riate Test Sta	atistics			
		F Statistics,	Num DF=5,	Den DF=145	4		
Variable	Total Standard Deviation	Pooled Standard Deviation	Between Standard Deviation	R-Square	R-Square / (1-RSq)	F Value	Pr > F
log_saleprice	0.3995	0.3339	0.2410	0.3037	0.4361	126.81	<.0001
lotfrontage	20.1000	19.8817	3.4772	0.0250	0.0256	7.44	<.0001
overallqual	1.3830	1.1293	0.8772	0.3355	0.5049	146.83	<.0001
overallcond	1.1128	1.0459	0.4216	0.1197	0.1360	39.53	<.0001
yearbuilt	30.2029	19.6159	25.1807	0.5796	1.3789	400.98	<.0001
yearremodadd	20.6454	16.8902	13.0461	0.3330	0.4992	145.18	<.0001
log_masvnrarea	2.6135	2.4929	0.8739	0.0932	0.1028	29.90	<.0001
bsmtfinsf1	435.2895	420.7455	125.1297	0.0689	0.0740	21.52	<.0001
bsmtunfsf	441.8670	418.8021	156.6076	0.1048	0.1170	34.03	<.0001
totalbsmtsf	418.2740	374.8027	204.7443	0.1998	0.2497	72.61	<.0001
log_x2ndfirsf	3.2933	3.2004	0.8749	0.0589	0.0625	18.18	<.0001
grlivarea	496.1339	473.1157	166.3551	0.0938	0.1035	30.08	<.0001
kitchenabvgr	0.2063	0.1972	0.0677	0.0899	0.0988	28.73	<.0001
totrmsabvgrd	1.6254	1.5875	0.3954	0.0493	0.0519	15.09	<.0001
garageyrblt	23.9946	17.6747	17.8067	0.4593	0.8493	246.98	<.0001
garagecars	0.7473	0.6645	0.3769	0.2121	0.2692	78.28	<.0001
garagearea	213.8048	196.2095	93.8589	0.1607	0.1915	55.68	<.0001
openporchsf	61.1182	58.9561	18.0448	0.0727	0.0784	22.80	<.0001
log_miscval	1.1683	1.1576	0.1885	0.0217	0.0222	6.45	<.0001

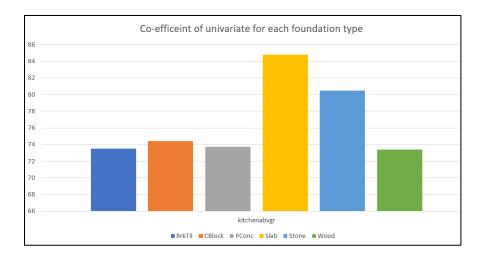
We can note the dependent variables included in the model have pvalues < 0.01, making them all signification in classifying the foundation type.

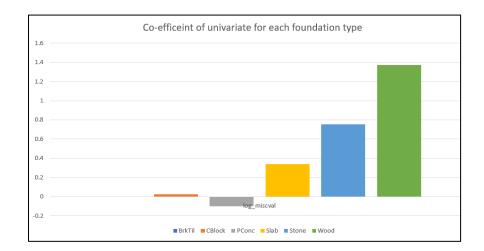
# LDA score for each foundation type:

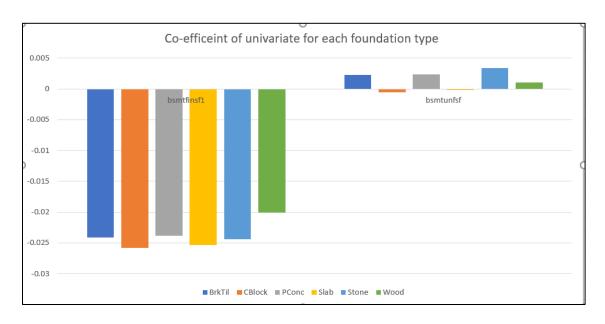
	Linea	r Discriminan	t Function fo	or foundation		
Variable	BrkTil	CBlock	PConc	Slab	Stone	Wood
Constant	-12738	-12935	-13174	-12969	-12758	-13205
log_saleprice	218.23800	217.92699	220.49971	221.18633	220.20438	207.08187
lotfrontage	0.67947	0.70881	0.69563	0.71612	0.67222	0.82314
overaliqual	-68.13145	-69.17323	-68.59344	-68.84250	-68.50602	-67.79816
overallcond	-7.62658	-6.97092	-7.87450	-8.25044	-7.00043	-6.83491
yearbuilt	3.00656	3.15990	3.17716	3.18482	2.98795	3.26491
yearremodadd	5.21780	5.17542	5.22318	5.15534	5.23066	5.23261
log_masvnrarea	-6.16668	-5.99265	-6.21283	-6.07605	-6.22185	-6.72188
bsmtfinsf1	-0.02415	-0.02578	-0.02388	-0.02538	-0.02437	-0.02005
bsmtunfsf	0.00222	-0.0006017	0.00234	-0.0002185	0.00335	0.00105
totalbsmtsf	-0.00691	-0.00491	-0.00722	-0.02505	-0.00820	-0.00870
log_x2ndflrsf	6.81118	6.68527	6.86850	5.04112	6.72852	7.09369
grlivarea	-0.03490	-0.03332	-0.03447	-0.02501	-0.03416	-0.02715
kitchenabvgr	73.48621	74.43396	73.75574	84.77637	80.50236	73.38054
totrmsabvgrd	1.02602	0.90734	0.85179	0.97275	1.09025	0.09840
garageyrblt	3.73369	3.72606	3.76881	3.71416	3.72852	3.75051
garagecars	-60.44115	-61.49126	-60.84745	-60.82226	-60.38015	-61.29631
garagearea	-0.06953	-0.06862	-0.07057	-0.06863	-0.06697	-0.06782
openporchsf	-0.27703	-0.27611	-0.27406	-0.27539	-0.26729	-0.29041
log_miscval	-0.00523	0.02361	-0.10301	0.33745	0.75381	1.37211

Looking at the co-efficients, Bsntunsf and log\_misCval are good classifier for foundation. Totrmsabvfrg, garagearea helps to differenciate the foundation types.

To understand the co-efficent better, Below are the plots that visually show the difference in co-efficient for a particular variable.







### **Classification summary**

		assificat substitut		Summ	ary		alibra	tion	Data:									
	Num	ber of O	bse	rvatio	ıs aı	nd Pe	rcent	Clas	ssified	int	o found	lati	on					
From fo	undation	Brk	Til	CBlo	ck	PC	onc		Slab		Stone		Wood	Total				
BrkTil		91.	33 10	5.	8 48	(	0.00	0.00			5 3.42		0.00	146 100.00				
CBlock		13.	86 56	69.	38 09	15	99 5.62		9 1.42		1 0.16		1 0.16	634 100.00				
PConc		44 6.80		39 6.03			557 6.09	3 0.46		0.31			2 0.31	647 100.00				
Slab		0 0.00		8.	2 33	1 4.17		8	21 87.50		0.00		0.00	24 100.00				
Stone		2 33.33							0.00		3 50.00		0.00	100.00				
Wood		0.	0	0.	0.00		-		-		1 3.33 (		0.00		0.00		2 66.67	100.00
Total		2 18.	65 15	33.	88 42		658 5.07		33 2.26		11 0.75		5 0.34	1460 100.00				
Priors		0.42254			85	0.41	596	0.0	1502	0.	00376	0.	00188					
			Erre	or Cou	ınt F	etima	itas f	or fo	undati	on			<u>'</u>	1				
		BrkTil				onc		lab	or foundation				Total					
	Rate 0.0890 Priors 0.4225			3091		1391	0.1		0.500		0.3333	-	0.1434					
			0			4160 0.01						9						

- Out of 146 BrkTil Type only 133 got classified correctly.
- 5% of BrkTile ended up as CBlock.
- 86% of CBlock was accurately classified.
- A high % of misclassification of CBlock is PConc with 15%.
- Overall error rate is 0.14% making an accuracy of this model to 86%

### Test data results:

			_	.,		ъ.	rı c	-			1			
			Observation Profile for Test Data  Number of Observations Read   1459											
										1459				
			Nun	nber o	f Ob	serva	tions	Used	1 1	1459				
	Num	ber of O	)bse	rvatio	ıs aı	nd Pe	rcent	Class	sifie	d into	found	latio	n	
From fo	oundation	Brk	Til	CBlo	ck	PC	onc	S	lab	9	Stone	W	lood	Tota
BrkTil		90.	50 91	6	10 .06	(	1 0.61	3 1.82			1 0.61		0.00	165 100.00
CBlock			70 65			14	90 4.98			0.33			2 0.33	601 100.00
PConc			46 45 6.96 6.81			561 84.87		(	2 0.30 0.30		_		5 0.76	661 100.00
Slab		0.	0 2 .00 8.00		0.00		92	23 92.00		0.00		0.00	25 100.00	
Stone		80.	4 0 0.00 0.00		00.00	, , , ,		0.00			20.00		0.00	100.00
Wood		0.	00	0.00		2 100.00		(	0.00		0.00		0.00	100.00
Total		18.	.70 .51	479 32.83			654 4.83	2	43 2.95		6 0.41		7 0.48	1459 100.00
Priors	Priors 0.42			0.140	85	0.41	596	0.01	502	0.0	0376	0.0	0188	
			_	-										
		BrkTil	Error Count Estimates for foundated CBlock   PConc   Slab   Store				ndat Sto		Wood		Total			
	Rate	0.0909		2978		1513	0.0		0.80		1.0000	-	.1494	
	race	0.0303	٠.	2010	٥.	1010	0.0	000	0.00		1.0000	,   0	. 1454	

Pattern of classification of test is very similar to train data.

- BrkTil has accuretly classified to 90%.
- A large % of misclassification on BrkTil is CBlock.
- A large % of misclassification on CBlock is Pconc type, 14%.
- Overall error rate is 0.15 making accuracy of the result to 85%.

### **Conclusion:**

The goal of this project was to the best of knowledge apply LDA as a classification technique (and hence impute the missing variables). The model built accurately classifies 85% of the cases into correct foundation type.