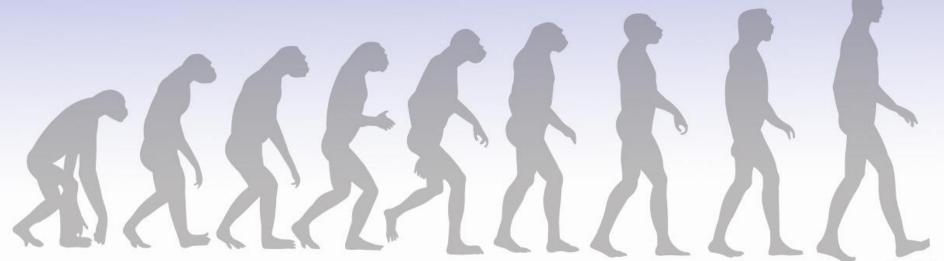


Gene Expression Level and Single Neuceutide Polymorphism Rates



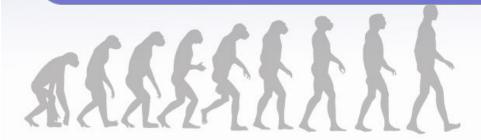


Protein Evolution in the past

Evolution rates controlled by "function-centered' Hypothesis



The functional importance of amino acid and their densities in a protein.



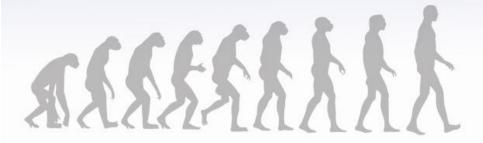


Factors affect the proteins evolution

The genomic position of the encoding genes

Gene expression patterns

 Position in biological networks and possibly their robustness to mistranslation.





Expression-based evolutionary analysis

Multicellular organisms

Using

Expression breadth

Unicellular organisms

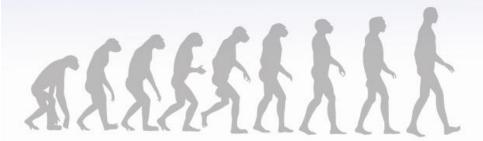
Using

Gene expression

Why "Expression breadth" used mainly in Multicellular organisms

 As Genes express at different levels in different tissue types in multicellular organisms.

 Therefore the Expression breadth is the number of different tissues where a gene is significantly expressed.





High Vs. Low

Low expressed genes

Involved in house-keeping processes

Weakly expressed

Higher and broader expressed, to have more interaction partners

Fewer interaction partners

Evolve slower, and are less prone to gene loss across various taxonomic groups

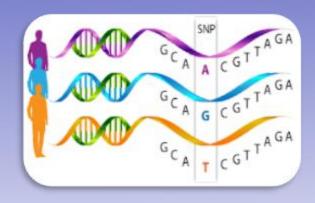
Genes evolve faster and are more often lost during evolution

Any mutation could be lethal

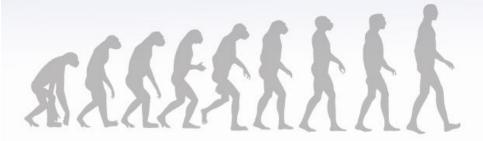


Single-nucleotide polymorphisms (SNPs)

 DNA base variants present in the human population at a frequency >1%.



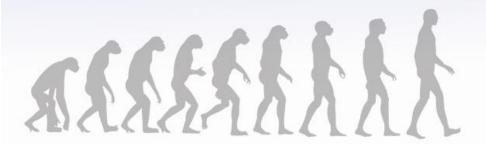
 The non-synonymous coding SNPs
 & SNPs in regulatory regions have an effect on phenotype.





Hypothesis

 Genes that are expressed at higher levels and in a greater number of tissues have lower single nucleotide polymorphism (SNP) rates than genes that are lowly/narrowly expressed.





Tools and Methods



Mygene



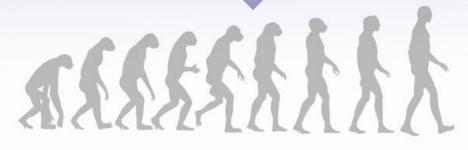
pybedtools



Pandas



Linux command line





Raw Data

	00Annotation	tpm.293SLAM%20rinderpest%20infection %2c%2000hr %2c%20biol_rep1.CNhs14406.13541-145H4	tpm.293SLAM%20rinderpest%20infection %2c%2000hr %2c%20biol_rep2.CNhs14407.13542-145H5	tpm.293SLAM%20rinderpest%20infection %2c%2000hr %2c%20biol_rep3.CNhs14408.13543-145H6
0	C9orf152	0.000000	0.000000	0.00000
1	ENST00000457273	0.000000	0.000000	0.000000
2	ELMO2	3.871942	6.530896	4.74557
3	RPS11	496.664564	504.874536	518.28468
4	CREB3L1	0.527992	0.907069	0.00000
5	PNMA1	78.846819	77.826510	72.37003
6	MMP2	0.000000	0.725655	0.67793
7	TMEM216	36.079460	35.738514	35.08336
8	TRAF3IP2-AS1	4.575931	5.623827	5.93197
9	C10orf90	0.000000	0.000000	0.00000

```
df['max_expr'] = df.iloc[:, 1:1829].max(axis=1)
df['median_expr'] = df.iloc[:, 1:1829].median(axis=1)
df['expr_breadth'] = df.iloc[:, 1:1829].ge(5, axis=0).sum(axis=1)
```





Max-Median-Breadth Calculations

	Annotation	max_expr	median_expr	expr_breadth
0	C9orf152	90.000000	90.0	3
1	ENST00000457273	2.349140	0.0	О
2	ELMO2	1695.000000	1695.0	3
3	RPS11	3314.932418	1826.0	3
4	CREB3L1	1021.000000	1021.0	3
5	PNMA1	1780.000000	1780.0	3
6	MMP2	8337.690244	1224.0	3
7	TMEM216	1553.000000	1553.0	3
8	TRAF3IP2-AS1	483.000000	483.0	3
9	C10orf90	1212.386209	121.0	3
10	ENST00000435872	7.363069	3.0	1





High/Low genes selection

- Sorting genes according to these values:
 - Max Expression.
 - Median Expression.
 - Expression Breadth.
- Selecting top 5% and low 5% of genes according to the calculated values.

	Annotation	max_expr	
0	HBB	1.400648e+06	
1	SMR3B	9.885506e+05	
2	STATH	8.895355e+05	
3	uc004cox.3	5.185081e+05	

		Annotation	median_expr
	0	uc004cos.3	11389.754997
	1	MALAT1	4958.169276
	2	ACTG1	4714.807306
	3	ACTB	4614.233458
	4	TPT1	2923.555044

	Annotation	expr_breadth
0	C9orf152	3
1	ANXA8L2	3
2	ENST00000450990	3
3	ENST00000522897	3
4	NTAN1	3
5	C12orf4	3
		3

high_genes = set(df2['Annotation'][:1403])
low genes = set(df2['Annotation'][-1403:])

3

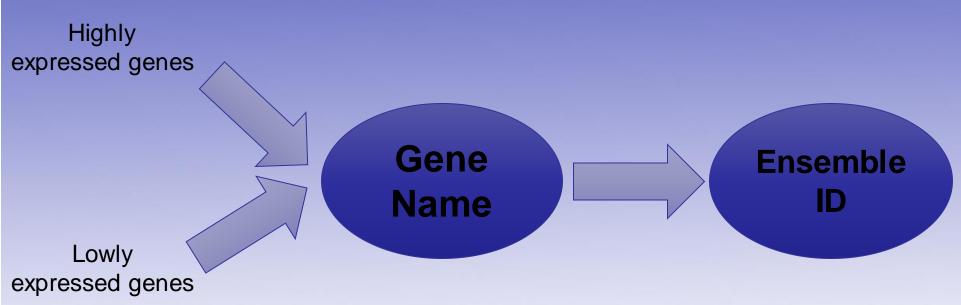


Gene Transfer Format of the hg19/GRCh37 genome

	0	1	2	3	4	5	6	7	8
0	1	pseudogene	gene	11869	14412		+	,	gene_id "ENSG00000223972"; gene_name "DDX11L1"
1	1	processed_transcript	transcript	11869	14409		+		gene_id "ENSG00000223972"; transcript_id "ENST
2	1	processed_transcript	exon	11869	12227		+		gene_id "ENSG00000223972"; transcript_id "ENST
3	1	processed_transcript	exon	12613	12721		+		gene_id "ENSG00000223972"; transcript_id "ENST
4	1	processed_transcript	exon	13221	14409		+		gene_id "ENSG00000223972"; transcript_id "ENST
5	1	transcribed_unprocessed_pseudogene	transcript	11872	14412		+		gene_id "ENSG00000223972"; transcript_id "ENST
6	1	transcribed_unprocessed_pseudogene	exon	11872	12227		+		gene_id "ENSG00000223972"; transcript_id "ENST
7	1	transcribed_unprocessed_pseudogene	exon	12613	12721		+		gene_id "ENSG00000223972"; transcript_id "ENST
8	1	transcribed_unprocessed_pseudogene	exon	13225	14412		+		gene_id "ENSG00000223972"; transcript_id "ENST
9	1	transcribed_unprocessed_pseudogene	transcript	11874	14409		+		gene_id "ENSG00000223972"; transcript_id "ENST
10	1	transcribed_unprocessed_pseudogene	exon	11874	12227		+		gene_id "ENSG00000223972"; transcript_id "ENST



Gene Names to Ensemble Gene Ds Conversion



```
def gene_to_ens(genes):
    mg = mygene.MyGeneInfo()
ENS_IDs = []
for gene in genes:
    result = mg.query(gene, scopes="symbol", fields=["ensembl"], species="human", verbose=False)
    hgnc_name = gene
    for hit in result["hits"]:
        if "ensembl" in hit and "gene" in hit["ensembl"]:
            ENS_IDs.append(hit["ensembl"]["gene"])
    return(ENS_IDs)
```



Gtf file for selected genes



```
def get_gtf(df_gtf, ens_ids):
    df_ = pd.DataFrame()
    for value in ens_ids:
        df_ = df_.append(df_gtf[df_gtf[8].str.contains(value)==True], ignore_index=True)
    return(df_)
```

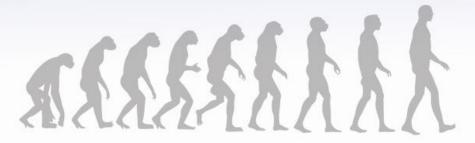
ARRAMA



Where is the coding regions????

Complete gtf for selected genes

Gtf selected genes(exons only)





SNPs file (VCF file)

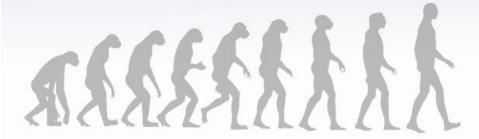
##fileformat=VCFv4.1
##fileDate=07/30/15
##source=SeqPilotV4.1.2
##INFO=<ID=TI,Number=.,Type=String,Description="Transcript ID">
##INFO=<ID=GI,Number=.,Type=String,Description="Gene ID">
##INFO=<ID=DB,Number=0,Type=Flag,Description="dbSNP membership: SNP137 - hg19 - 2012-12-18">
##FILTER=<ID=q15,Description="Quality below or equal15">
##FORMAT=<ID=GT,Number=1,Type=String,Description="Genotype">
##FORMAT=<ID=DP,Number=1,Type=Integer,Description="Read depth at this position for this sample">

##FORMAT=<ID=AF, Number=A, Type=Float, Description="Allele frequency for each ALT allele in the same order as listed">

#CHROM	P	OS ID	REF	ALT	QUAL	FILTER	INFO	FORMAT	51
	1	45794806 .	С	CT		PASS	TI=NM_001048171;GI=MUTYH	GT:DP:AF	0/1:265:0.51
	1	45796269 rs3219493	G	C	+:	PASS	TI=NM_001048171;GI=MUTYH;DB	GT:DP:AF	0/1:303:0.43
	1	45798555 rs3219487	T	C		PASS	TI=NM_001048171;GI=MUTYH;DB	GT:DP:AF	0/1:241:0.55
	1	45798699 .	AC	A		PASS	TI=NM_001048171;GI=MUTYH	GT:DP:AF	0/1:416:0.30
	1	45798726 .	TG	T		PASS	TI=NM_001048171;GI=MUTYH	GT:DP:AF	0/1:346:0.23
	10	88515072 rs3905377	T	C		PASS	TI=NR_031657_2;GI=MIR1256;DB	GT:DP:AF	1/1:544:1.00
	10	88515190 .	G	GT		PASS	TI=NR_031657_2;GI=MIR1256	GT:DP:AF	0/1:745:0.14
	10	88515790 .	т	TC		PASS	TI=NR_031657_2;GI=MIR1256	GT:DP:AF	0/1:352:0.11
	10	88515966 rs7070369	G	A		PASS	TI=NR_031657_2;GI=MIR1256;DB	GT:DP:AF	1/1:206:1.00
	10	88635779 rs3182217	C	A		PASS	TI=NM_004329;GI=BMPR1A;DB	GT:DP:AF	0/1:766:0.49
	10	88649763 rs7087358	C	T		PASS	TI=NM_004329;GI=BMPR1A;DB	GT:DP:AF	1/1:982:1.00
	10	88683122 rs7074064	T	c		PASS	TI=NM_004329;GI=BMPR1A;DB	GT:DP:AF	0/1:554:0.54
	10	88683724 .	G	A		PASS	TI=NM_004329;GI=BMPR1A	GT:DP:AF	0/1:410:0.25
	10	88683733 .	T	TT		PASS	TI=NM_004329;GI=8MPR1A	GT:DP:AF	0/1:422:0.40
	10	88683808 .	AA	A		PASS	TI=NM_004329;GI=BMPR1A	GT:DP:AF	0/1:423:0.13
	10	88683847.	C	T		PASS	TI=NM_004329;GI=BMPR1A	GT:DP:AF	0/1:417:0.28
	10	88683890 rs7078571	T	A		PASS	TI=NM_004329;GI=BMPR1A;DB	GT:DP:AF	1/1:402:0.99
	10	89623897 .	CCGTG	TCGTC		PASS	TI=NM_000314;GI=PTEN	GT:DP:AF	0/1:224:0.25
	10	89623901 rs2943772	G	C		PASS	TI=NM_000314;GI=PTEN;DB	GT:DP:AF	0/1:218:0.73
	10	89623944 .	CGGC	TGGA		PASS	TI=NM_000314;GI=PTEN	GT:DP:AF	0/1:231:0.26
	10	89624039 .	C	A		PASS	TI=NM_000314;GI=PTEN	GT:DP:AF	0/1:215:0.27
	10	89624045 .	A	C		PASS	TI=NM_000314;GI=PTEN	GT:DP:AF	0/1:213:0.26
	10	89685280 .	T	TA		PASS	TI=NM_000314;GI=PTEN	GT:DP:AF	0/1:655:0.30
	10	89685327 .	T	TT		PASS	TI=NM_000314;GI=PTEN	GT:DP:AF	0/1:716:0.19
	10	89690626 .	GG	G		PASS	TI=NM_000314;GI=PTEN	GT:DP:AF	0/1:144:0.11
	10	89690750 .	П	Т		PASS	TI=NM_000314:GI=PTFN	GT:DP:AF	0/1:137:0.14

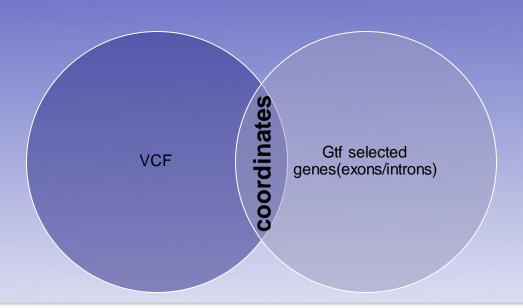
Get Exons/ Introns

```
!grep -P "\texon\t" GRCh37_filtered_high_med.gtf | bedtools sort > exons_high_med.gtf
!bedtools sort -i exons_high_med.gtf > sorted_exons_high_med.gtf
!bedtools merge -s -i sorted_exons_high_med.gtf -c 6,7 -o distinct,distinct > exons_high_med.bed
!grep -P "\ttranscript\t" GRCh37_filtered_high.gtf | bedtools sort > transcripts_high_med.gtf
!bedtools sort -i transcripts_high_med.gtf > sorted_transcripts_high_med.gtf
!bedtools merge -s -i transcripts_high_med.gtf -c 6,7 -o distinct,distinct > transcripts_high_med.bed
!bedtools subtract -a transcripts_high_med.bed -b exons_high_med.bed > introns_high_med.bed
```





Intersection

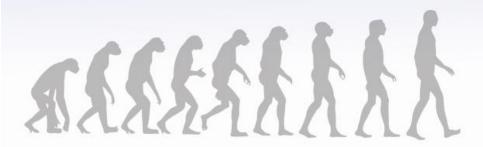


```
def get_SNPs(genes_bed_file):
    snps = BedTool('ALL.wgs.phase3_shapeit2_mvncall_integrated_v5b.20130502.sites.vcf.gz')
    expressed_genes = BedTool(genes_bed_file)
    expressed_genes.sort()
    SNPs = snps.intersect(expressed_genes)
    return(SNPs.count())
```



Results (exons)

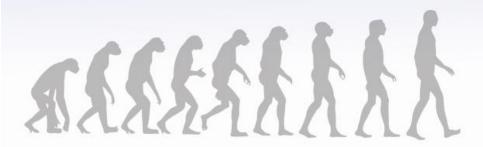
	Max Expression	Median Expression	Breadth Expression
Highly Expressed Genes	0.00348998373379 15773	0.0031972270987 368073	0.003228856553583
Lowly Expressed genes	0.00050077923754 17857	0.0014232640755 09528	0.028695393161306 672





Results (introns)

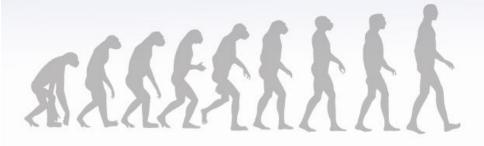
	Max Expression	Median Expression	Breadth Expression
Highly Expressed Genes	0.03314763184341 043	0.0282721036324 3538	0.000502768356984 7616
Lowly Expressed genes	0.00985862849256 6827	0.0237316683765 11285	0.009577278598021 467





Conclusion

- According to exons: SNPs frequency inversely proportional gene expression mainly according to breadth
- While according to introns: SNPs frequency inversely proportional gene expression mainly according to breadth



What else?

 We can conclude a new hypothesis that the SNPs in noncoding regions can associated with number of diseases, this improves our understanding of noncoding of genomes and their roles in disease.

Identifying noncoding risk variants using disease-relevant gene regulatory networks

Long Gao, Yasin Uzun, Peng Gao, Bing He, Xiaoke Ma, Jiahui Wang, Shizhong Han & Kai Tan 🖾

Nature Communications 9, Article number: 702 (2018) | Download Citation ±

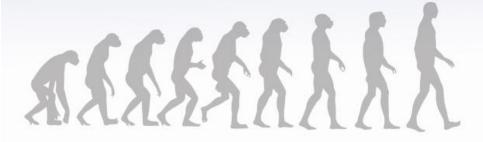


Recommendation

This all steps can be done using:







THANK YOU

