

# main\_\_exons

September 2, 2021

## 1 Enrichment and Overlap of PGC2+CLOZUK

```
[1]: import re
import os, errno
import functools
import numpy as np
import pandas as pd
from plotnine import *
from pandas_plink import read_plink
from warnings import filterwarnings
from matplotlib.cbook import mplDeprecation
from scipy.stats import fisher_exact, binom_test

filterwarnings("ignore", category=mplDeprecation)
filterwarnings('ignore', category=UserWarning, module='plotnine.*')
filterwarnings('ignore', category=DeprecationWarning, module='plotnine.*')
```

### 1.1 Config and Functions

```
[2]: config = {
    'biomart_file': '../_h/biomart.csv',
    'phenotype_file': '/ceph/projects/v4_phase3_paper/inputs/phenotypes/_m/
    ↪merged_phenotypes.csv',
    'plink_file_prefix': '/ceph/projects/v4_phase3_paper/inputs/genotypes/_m/
    ↪LIBD_Brain_TopMed',
    'gwas_snp_file': '/ceph/projects/v4_phase3_paper/inputs/sz_gwas/pgc2_clozuk/
    ↪map_phase3/_m/libd_hg38_pgc2sz_snps.tsv',
    'exon_annotation': "../_h/exons.csv"
}

config_feature = {
    'de_file': '../../differential_expression/_m/exons/diffExpr_szVctl_full.
    ↪txt',
    'residual_expression_file': '../../differential_expression/_m/exons/
    ↪residualized_expression.tsv',
    'fastqtl_output_file': '../../eqtl/caudate/summary_table/_m/
    ↪Brainseq_LIBD_caudate_4features.signifpairs.txt.gz',
```

```
}

feature = "exons"
```

```
[3]: @functools.lru_cache()
def get_exon_annot():
    return pd.read_csv(config['exon_annotation'])

@functools.lru_cache()
def feature_map(feature):
    return {"genes": "Gene", "transcripts": "Transcript",
            "exons": "Exon", "junctions": "Junction"}[feature]

@functools.lru_cache()
def get_de_df():
    """
    Load DE analysis
    """
    return pd.read_csv(config_feature['de_file'], sep='\t', index_col=0)

@functools.lru_cache()
def get_eqtl_df():
    eqtl_df = pd.read_csv(config_feature['fastqtl_output_file'], sep='\t')
    return eqtl_df[(eqtl_df["Type"] == feature_map(feature))]

@functools.lru_cache()
def get_gwas_snps():
    return pd.read_csv(config['gwas_snp_file'], sep='\t', index_col=0,
        ↳ low_memory=False)

@functools.lru_cache()
def get_integration_df():
    return get_gwas_snps().merge(get_eqtl_df(), left_on='our_snp_id',
        ↳ right_on='variant_id',
                                suffixes=['_PGC2', '_eQTL'])\
        .merge(get_de_df(), left_on='gene_id',
        ↳ right_index=True)

@functools.lru_cache()
def get_residual_expression_df():
    return pd.read_csv(config_feature['residual_expression_file'],
```

```
sep='\t', index_col=0).transpose()
```

```
@functools.lru_cache()
def get_pheno_df():
    return pd.read_csv(config['phenotype_file'], index_col=0)
```

```
[4]: def agree_direction(row):
    return [-1, 1][row['pgc2_a1_same_as_our_counted']] * np.sign(row['OR'] - 1)
    ↪ * np.sign(row['slope']) * np.sign(row['t'])
```

```
def save_plot(p, fn):
    for ext in ['png', 'pdf', 'svg']:
        p.save(fn + '.' + ext)
```

```
def letter_snp(number, a0, a1):
    '''
    Example:
    letter_snp(0, 'A', 'G') is 'AA'
    letter_snp(1, 'A', 'G') is 'AG'
    letter_snp(2, 'A', 'G') is 'GG'

    '''
    if np.isnan(number):
        return np.nan

    if len(a0)==1 and len(a1)==1:
        sep = ''
    else:
        sep = ' '
    return sep.join(sorted([a0]*int(number) + [a1]*(2-int(number)))))
```

```
def get_gwas_snp(snp_id):
    gwas = get_gwas_snps()
    r = gwas[gwas['our_snp_id']==snp_id]
    assert len(r) == 1
    return r
```

```
[5]: @functools.lru_cache()
def get_expression_and_pheno_df():
    return pd.merge(get_pheno_df(), get_residual_expression_df(),
    ↪ left_index=True, right_index=True)
```

```

@functools.lru_cache()
def get_plink_tuple():
    """
    Usage: (bim, fam, bed) = get_plink_tuple()
    """
    return read_plink(config['plink_file_prefix'])

@functools.lru_cache()
def subset_bed():
    """
    This subsets the bed and bim file and returns the new subsetted
    data with shared brain_ids.

    This is to speed up accessing the bed file.
    """
    (bim, fam, bed) = get_plink_tuple()
    brain_ids = list(set(get_expression_and_pheno_df()['BrNum'])).
    ↪ intersection(set(fam['fid'])))
    fam_pos = list(fam[(fam["fid"].isin(brain_ids))]).
    ↪ drop_duplicates(subset="fid").loc[:, 'i'])
    unique_snps = get_eqtl_df().variant_id.unique()
    snp_info = bim[(bim["snp"].isin(unique_snps))].copy()
    snp_pos = list(snp_info.loc[:, "i"])
    new_bed = bed[snp_pos].compute()[:, fam_pos]
    new_bim = bim[(bim["i"].isin(snp_pos))].reset_index(drop=True)
    new_bim['ii'] = new_bim.index
    return new_bed, new_bim, brain_ids

@functools.lru_cache()
def get_snp_df(snp_id):
    """
    Returns a dataframe containing the genotype on snp snp_id.
    The allele count is the same as in the plink files.

    Example:
    get_snp_df('rs653953').head(5)

        rs653953_num rs653953_letter rs653953
    Br5168          0             GG    0\nGG
    Br2582          1             AG    1\nAG
    Br2378          1             AG    1\nAG
    Br5155          2             AA    2\nAA
    Br5182          2             AA    2\nAA
    """
    bed, bim, brain_ids = subset_bed()

```

```

snp_info = bim[bim['snp']==snp_id]
snp_pos = snp_info.iloc[0]['ii']
dfsnp = pd.DataFrame(bed[[snp_pos]], columns=brain_ids, index=[snp_id +
↳ '_num']).transpose().dropna()
my_letter_snp = functools.partial(letter_snp, a0=snp_info.iloc[0]['a0'],
↳ a1=snp_info.iloc[0]['a1'])
# the 2 - in next line is to workaround a possible bug in pandas_plink? a1
↳ and a0 inverted
dfsnp[[snp_id + '_num']] = 2 - dfsnp[[snp_id + '_num']].astype('int')
dfsnp[snp_id + '_letter'] = dfsnp[snp_id + '_num'].apply(my_letter_snp)
dfsnp[snp_id] = (dfsnp[snp_id + '_num'].astype('str') + '\n' +
                 dfsnp[snp_id + '_letter'].astype('str')).astype('category')
return dfsnp

@functools.lru_cache()
def get_gwas_ordered_snp_df(snp_id):
    '''
    Returns a dataframe containing the genotype on snp snp_id.
    The allele count is the number of risk alleles according to GWAS.

    Example:
    get_gwas_ordered_snp_df('rs653953').head(5)

           rs653953_num rs653953_letter rs653953
    Br5168             2             GG      2\nGG
    Br2582             1             AG      1\nAG
    Br2378             1             AG      1\nAG
    Br5155             0             AA      0\nAA
    Br5182             0             AA      0\nAA
    '''
    pgc = get_gwas_snps()
    dfsnp = get_snp_df(snp_id).copy()
    gwas_snp = get_gwas_snp(snp_id)

    if gwas_snp['pgc2_a1_same_as_our_counted'].iloc[0]:
        if gwas_snp['OR'].iloc[0] > 1:
            pass
        else:
            dfsnp[[snp_id + '_num']] = 2 - dfsnp[[snp_id + '_num']]
    else:
        if gwas_snp['OR'].iloc[0] > 1:
            dfsnp[[snp_id + '_num']] = 2 - dfsnp[[snp_id + '_num']]
        else:
            pass

    dfsnp[snp_id] = (dfsnp[snp_id + '_num'].astype('str') + '\n' +

```

```

dfsnp[snp_id + '_letter'].astype('str')).astype('category')
return dfsnp

```

```

[6]: @functools.lru_cache()
def get_biomart_df():
    biomart = pd.read_csv(config['biomart_file'])
    biomart['description'] = biomart['description'].str.replace('\[Source.
↳*$', '', regex=True)
    return biomart

def get_gene_symbol(gene_id, biomart=get_biomart_df()):
    ensge = re.sub('\..+$', '', gene_id)
    ggg = biomart[biomart['ensembl_gene_id']==ensge]
    if ggg.shape[0]==0:
        return '', ''
    gs = ggg['external_gene_name'].values[0]
    de = ggg['description'].values[0]
    if type(de)!=str:
        de = ''
    de = re.sub('\[Source:.*$', '', de)
    return gs, de

@functools.lru_cache()
def get_risk_allele(snp_id):
    gwas_snp = get_gwas_snp(snp_id)
    if gwas_snp['OR'].iloc[0] > 1:
        ra = gwas_snp['A1'].iloc[0]
    else:
        ra = gwas_snp['A2'].iloc[0]
    return ra

```

```

[7]: def get_snp_gene_pheno_df(snp_id, gene_id, snp_df_func):
    pheno_columns = list(get_pheno_df().columns)
    expr_df = get_expression_and_pheno_df()[pheno_columns + [gene_id]]
    snp_df = snp_df_func(snp_id)
    return expr_df.merge(snp_df, left_on='BrNum', right_index=True)

def simple_snp_expression_pheno_plot_impl(snp_id, gene_id, snp_df_func,
↳pheno_var):
    df = get_snp_gene_pheno_df(snp_id, gene_id, snp_df_func)
    df['Dx'] = df.Dx.astype('category').cat.rename_categories({'Control':
↳'CTL', 'Schizo': 'SZ'})
    y0 = df[gene_id].quantile(.01) - 0.26
    y1 = df[gene_id].quantile(.99) + 0.26

```

```

pjd = position_jitterdodge(jitter_width=0.27)
p = ggplot(df, aes(x=snp_id, y=gene_id, fill=pheno_var)) \
+ geom_boxplot(alpha=0.4, outlier_alpha=0) \
+ geom_jitter(position=pjd, stroke=0, alpha=0.6) + ylim(y0, y1) \
+ labs(y='Residualized expression', fill='Diagnosis') \
+ theme_bw(base_size=20)\
+ theme(legend_title=element_text(face='bold'),
        panel_grid_major=element_blank(),
        panel_grid_minor=element_blank())
return p

def simple_gwas_ordered_snp_expression_pheno_plot(snp_id, gene_id, pheno_var):
    return simple_snp_expression_pheno_plot_impl(snp_id, gene_id,
    ↪get_gwas_ordered_snp_df, pheno_var)

```

```

[8]: def exon_annotation(gene_id):
    return get_exon_annot()[get_exon_annot().brainseq_exon_id == gene_id].
    ↪exon_id.values[0]

def gwas_annotation(snp_id):
    return 'SZ GWAS pvalue: %.1e' % get_gwas_snp(snp_id).iloc[0]['P']

def eqtl_annotation(snp_id, gene_id):
    r = get_eqtl_df()[get_eqtl_df()['variant_id']==snp_id] &
    (get_eqtl_df()['gene_id']==gene_id)]
    assert len(r)==1
    return 'eQTL nominal p-value: %.1e' % r.iloc[0]['pval_nominal']

def de_annotation(gene_id):
    de_df = get_de_df()
    de_df['Feature'] = de_df.index
    g = de_df[(de_df['Feature'] == gene_id)]
    return 'DE adj.P.Val: %.3f' % g.iloc[0]['adj.P.Val']

def risk_allele_annotation(snp_id):
    return 'SZ risk allele: %s' % get_risk_allele(snp_id)

def gwas_annotated_eqtl_pheno_plot(snp_id, gene_id, pheno_var):
    p = simple_gwas_ordered_snp_expression_pheno_plot(snp_id, gene_id,
    ↪pheno_var)
    de_df = get_de_df()

```

```

de_df['Feature'] = de_df.index
de_df = de_df[(de_df['Feature'] == gene_id)]
gene_symbol, gene_description = get_gene_symbol(de_df.iloc[0]['gencodeID'])
exon_id = exon_annotation(gene_id)
title = "\n".join([gene_symbol,
                    exon_id,
                    gwas_annotation(snp_id),
                    risk_allele_annotation(snp_id),
                    eqtl_annotation(snp_id, gene_id),
                    de_annotation(gene_id)])
p += ggtitle(title)
return p

```

## 1.2 Exons

```

[9]: try:
      os.makedirs(feature)
except OSError as e:
      if e.errno != errno.EEXIST:
          raise

```

### 1.2.1 Enrichment

#### Integrate DEG with PGC2+CLOZUK SNPs

```

[10]: dft = get_integration_df()
      dft.shape

```

/home/jbenja13/.local/lib/python3.9/site-packages/numpy/lib/arraysetops.py:583:  
FutureWarning: elementwise comparison failed; returning scalar instead, but in  
the future will perform elementwise comparison

```

[10]: (3650186, 52)

```

```

[11]: agreement = {1: 'Yes', -1: 'No', 0: 0}
      dft['agree_direction'] = dft.apply(agree_direction, axis=1)
      dft.agree_direction = [agreement[item] for item in dft['agree_direction']]

      table = [[np.sum((dft['P']<5e-8) & ((dft['adj.P.Val']<.05))),
                  np.sum((dft['P']<5e-8) & ((dft['adj.P.Val']>=.05))),
                  [np.sum((dft['P']>=5e-8) & ((dft['adj.P.Val']<.05))),
                    np.sum((dft['P']>=5e-8) & ((dft['adj.P.Val']>=.05)))]]
      print(table)
      fisher_exact(table)

```

```

[[3962, 67556], [256601, 3322067]]

```

```

[11]: (0.7592775985025325, 1.0709599924360984e-67)

```



```
[12]: dft1 = dft[(dft['P']<5e-8) & ((dft['adj.P.Val']<.05))]
df = dft1.groupby('agree_direction').size().reset_index()
df
```

```
[12]: agree_direction    0
0                No    574
1                Yes  3388
```

```
[13]: binom_test(df[0].iloc[1], df[0].sum())
```

```
[13]: 0.0
```

```
[14]: dft2 = dft[(dft['P']<=5e-8) & (dft['adj.P.Val'] < 0.05)].copy()
dft2['risk_allele'] = dft2['our_snp_id'].apply(get_risk_allele)
```

```
[15]: direction = {-1: 'Down', 1: 'Up'}
boolean_conv = {True: 1, False: -1}
dft2.pgc2_a1_same_as_our_counted = [boolean_conv[item] for item in
    ↪dft2['pgc2_a1_same_as_our_counted']]
dft2['eqtl_gwas_dir'] = [direction[item] for item in np.
    ↪sign(dft2['pgc2_a1_same_as_our_counted']) * np.sign(dft2['slope']) * np.
    ↪sign(dft2['OR'] - 1)]
dft2['de_dir'] = [direction[item] for item in np.sign(dft2['t'])]
dft2['eqtl_slope'] = np.sign(dft2['pgc2_a1_same_as_our_counted']) * np.
    ↪sign(dft2['OR'] - 1) * dft2['slope']
dft2 = dft2[['gene_id', 'Symbol', 'variant_id', 'A1', 'A2', 'risk_allele', 'OR',
    'P', 'pval_nominal', 'adj.P.Val', 'logFC', 't', 'eqtl_slope',
    'de_dir', 'eqtl_gwas_dir', 'agree_direction']]
dft2['Symbol'].fillna(dft2['gene_id'], inplace=True)
dft2.to_csv('%s/integration_by_symbol.txt' % feature, sep='\t', index=False)
```

```
[16]: df2 = dft2.groupby(['Symbol']).first().reset_index().sort_values('P')
df2.groupby('agree_direction').size()
```

```
[16]: agree_direction
No      11
Yes     14
dtype: int64
```

```
[17]: df2.set_index('Symbol').rename(columns={'t': 'de_t', 'P': 'GWAS_P',
    ↪'pval_nominal': 'eQTL_pvalue',
    'adj.P.Val': 'de_FDR'})
```

```
[17]:
```

	gene_id	variant_id	A1	A2	risk_allele	OR	\
Symbol							
HCG4	e379384	chr6:29292654:C:T	C	T	C	1.26140	
ZNF391	e378375	chr6:27003116:C:A	C	A	C	1.19440	

FLOT1	e380557	chr6:30261490:G:C	G	C	G	1.23800
BRD2	e386363	chr6:32634921:C:T	C	T	C	1.17320
ZSCAN26	e378558	chr6:27772887:C:T	C	T	C	1.10460
PPP1R10	e380196	chr6:30856674:T:C	T	C	T	1.12860
HCG11	e378174	chr6:26466161:G:A	G	A	A	0.91432
ATF6B	e385196	chr6:31636233:C:G	C	G	G	0.92349
NGEF	e193333	chr2:232920039:T:G	T	G	G	0.92446
PLCH2	e4214	chr1:2440958:A:G	A	G	G	0.92873
e805477	e805477	chr14:103551456:G:A	G	A	A	0.93503
SLC35G2	e251472	chr3:136789166:C:A	C	A	A	0.94040
ZNF204P	e378369	chr6:27399042:C:A	C	A	C	1.06050
CNNM2	e598887	chr10:102825368:C:A	C	A	C	1.06040
PCCB	e251235	chr3:136088767:G:T	G	T	T	0.94493
ZFYVE21	e805625	chr14:103541822:C:T	C	T	T	0.93994
HIRIP3	e880446	chr16:29959536:C:G	C	G	C	1.05670
PPM1M	e226757	chr3:52253452:G:T	G	T	G	1.05600
ZC3H7B	e1136648	chr22:41357599:G:A	G	A	A	0.94102
REEP2	e353080	chr5:138362610:C:T	C	T	C	1.05600
IP6K3	e387950	chr6:33726302:C:T	C	T	C	1.07170
B3GAT1	e678063	chr11:134426490:C:T	C	T	C	1.05480
SLC7A6	e897871	chr16:68251944:A:G	A	G	G	0.93292
ZNF14	e1037535	chr19:19623068:T:C	T	C	T	1.06130
LINC01470	e361367	chr5:152550275:T:C	T	C	T	1.06120

	GWAS_P	eQTL_pvalue	de_FDR	logFC	de_t \
Symbol					
HCG4	6.890000e-39	4.889500e-05	1.888890e-02	0.225849	3.403813
ZNF391	1.330000e-30	8.931290e-05	3.050985e-02	0.089084	3.198447
FLOT1	4.410000e-27	2.234560e-04	4.343551e-02	-0.056802	-3.035928
BRD2	1.050000e-22	1.767730e-04	4.566092e-02	-0.055920	-3.012771
ZSCAN26	1.180000e-18	4.878850e-04	1.907918e-02	-0.084425	-3.399939
PPP1R10	2.320000e-17	2.833910e-04	3.267149e-02	-0.097099	-3.167716
HCG11	1.020000e-14	2.926190e-06	1.114014e-03	0.123153	4.437634
ATF6B	1.580000e-13	5.443640e-05	4.105628e-02	-0.077310	-3.062621
NGEF	2.030000e-13	3.210140e-05	3.934485e-02	0.094485	3.083163
PLCH2	4.630000e-11	2.092640e-08	2.092699e-03	-0.183916	-4.228084
e805477	2.500000e-10	2.159220e-04	4.326236e-02	0.088201	3.037782
SLC35G2	6.440000e-10	2.369150e-04	1.775019e-02	0.087134	3.429320
ZNF204P	6.470000e-10	2.912170e-04	2.730366e-02	0.101791	3.247301
CNNM2	1.120000e-09	1.275560e-10	1.824329e-03	0.082170	4.275115
PCCB	5.050000e-09	2.777040e-04	4.550772e-02	-0.086627	-3.014289
ZFYVE21	6.910000e-09	4.960450e-05	1.172012e-03	0.120871	4.421534
HIRIP3	1.190000e-08	5.943010e-05	1.852549e-02	-0.086915	-3.411509
PPM1M	1.350000e-08	2.619140e-04	6.255691e-03	-0.112520	-3.838539
ZC3H7B	1.760000e-08	3.336000e-05	2.460607e-02	-0.069774	-3.293462
REEP2	1.860000e-08	2.256820e-07	9.024244e-08	0.146930	6.740507
IP6K3	2.460000e-08	5.035440e-06	2.516434e-02	-0.206644	-3.283807

B3GAT1	2.980000e-08	2.428260e-05	5.232855e-03	-0.095884	-3.902576
SLC7A6	3.560000e-08	1.304730e-04	2.399729e-02	0.074993	3.304797
ZNF14	4.300000e-08	1.046650e-06	1.193200e-02	0.089690	3.587360
LINC01470	4.470000e-08	1.436330e-11	7.415818e-03	0.475060	3.772128

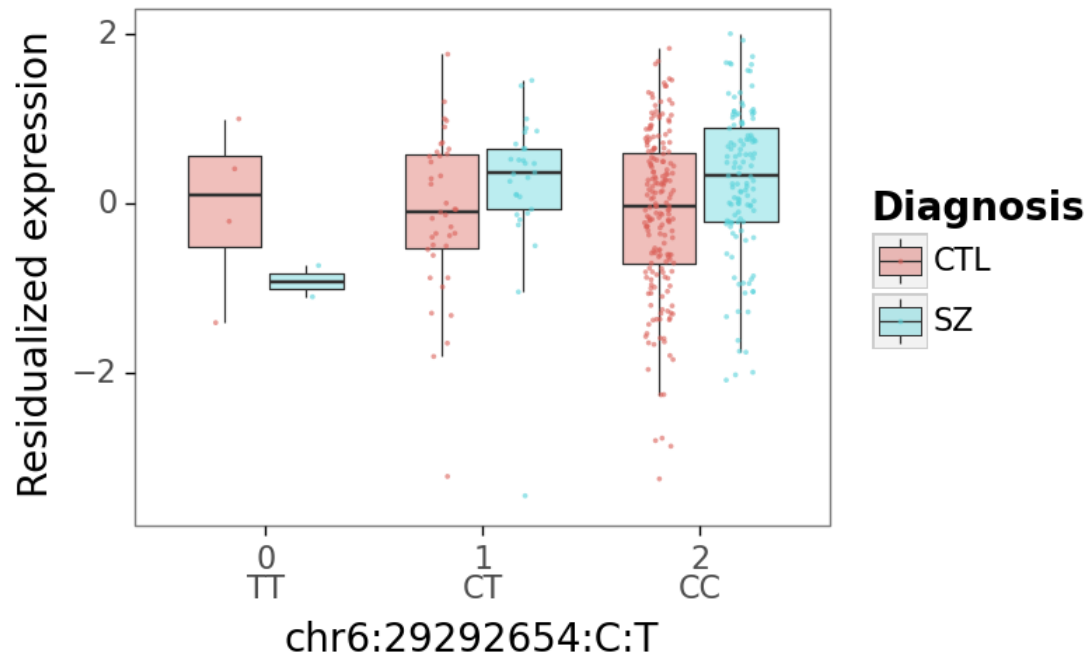
Symbol	eqtl_slope	de_dir	eqtl_gwas_dir	agree_direction
HCG4	0.376665	Up	Up	Yes
ZNF391	-0.248239	Up	Down	No
FLOT1	-0.181652	Down	Down	Yes
BRD2	-0.263443	Down	Down	Yes
ZSCAN26	-0.208406	Down	Down	Yes
PPP1R10	0.197282	Down	Up	No
HCG11	0.242904	Up	Up	Yes
ATF6B	0.205829	Down	Up	No
NGEF	-0.124147	Up	Down	No
PLCH2	-0.177917	Down	Down	Yes
e805477	0.160045	Up	Up	Yes
SLC35G2	-0.145741	Up	Down	No
ZNF204P	0.118762	Up	Up	Yes
CNNM2	-0.172984	Up	Down	No
PCCB	-0.175844	Down	Down	Yes
ZFYVE21	0.229127	Up	Up	Yes
HIRIP3	0.207663	Down	Up	No
PPM1M	-0.126091	Down	Down	Yes
ZC3H7B	0.185178	Down	Up	No
REEP2	0.162459	Up	Up	Yes
IP6K3	0.184969	Down	Up	No
B3GAT1	0.115385	Down	Up	No
SLC7A6	-0.155408	Up	Down	No
ZNF14	0.248788	Up	Up	Yes
LINC01470	0.400474	Up	Up	Yes

### 1.2.2 Plot with PGC2 risk allele

```
[18]: for xx in range(df2.shape[0]):
        gg = gwas_annotated_eqtl_pheno_plot(df2.iloc[xx, :].variant_id, df2.
        ↪iloc[xx, :].gene_id, 'Dx')
        print(gg)
        label = '%s/eqtl_gwas_%s' % (feature, df2.iloc[xx, :].Symbol)
        save_plot(gg, label)
```

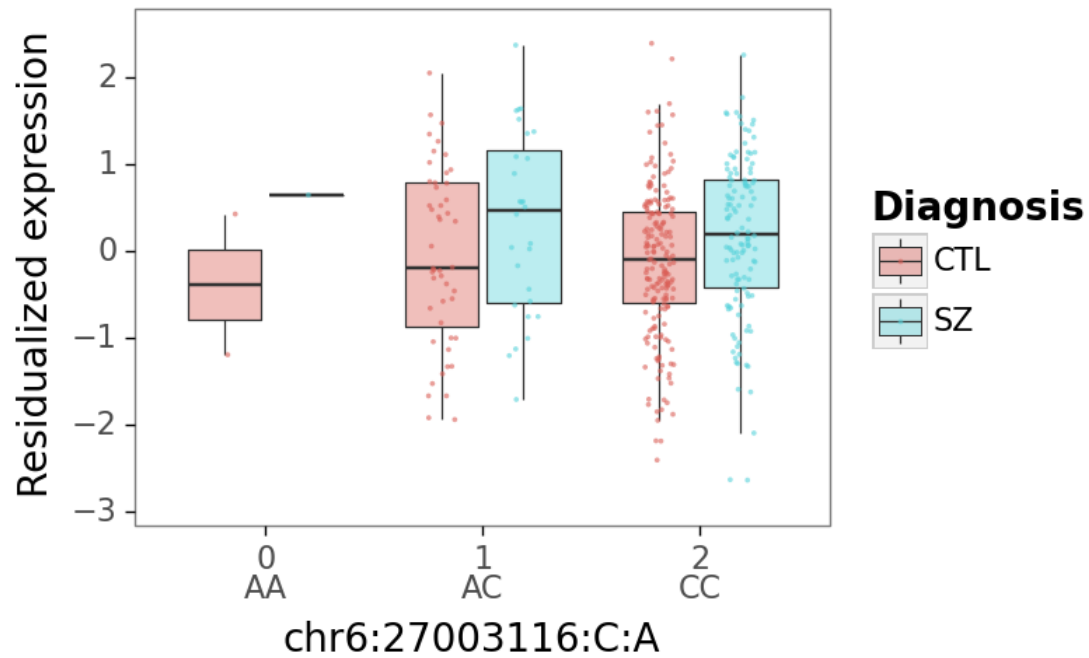
Mapping files: 100%| | 3/3 [00:25<00:00, 8.55s/it]

HCG4  
 ENSE00001735745.1  
 SZ GWAS pvalue: 6.9e-39  
 SZ risk allele: C  
 eQTL nominal p-value: 4.9e-05  
 DE adj.P.Val: 0.019



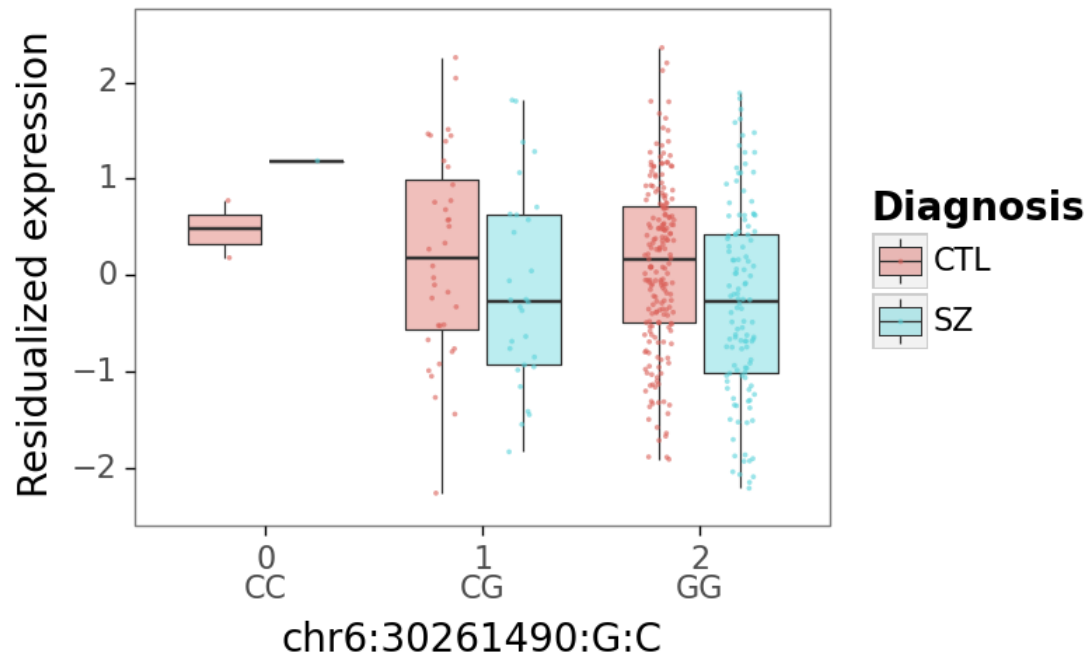
<ggplot: (8728654748703)>

ZNF391  
 ENSE00001733042.2  
 SZ GWAS pvalue: 1.3e-30  
 SZ risk allele: C  
 eQTL nominal p-value: 8.9e-05  
 DE adj.P.Val: 0.031



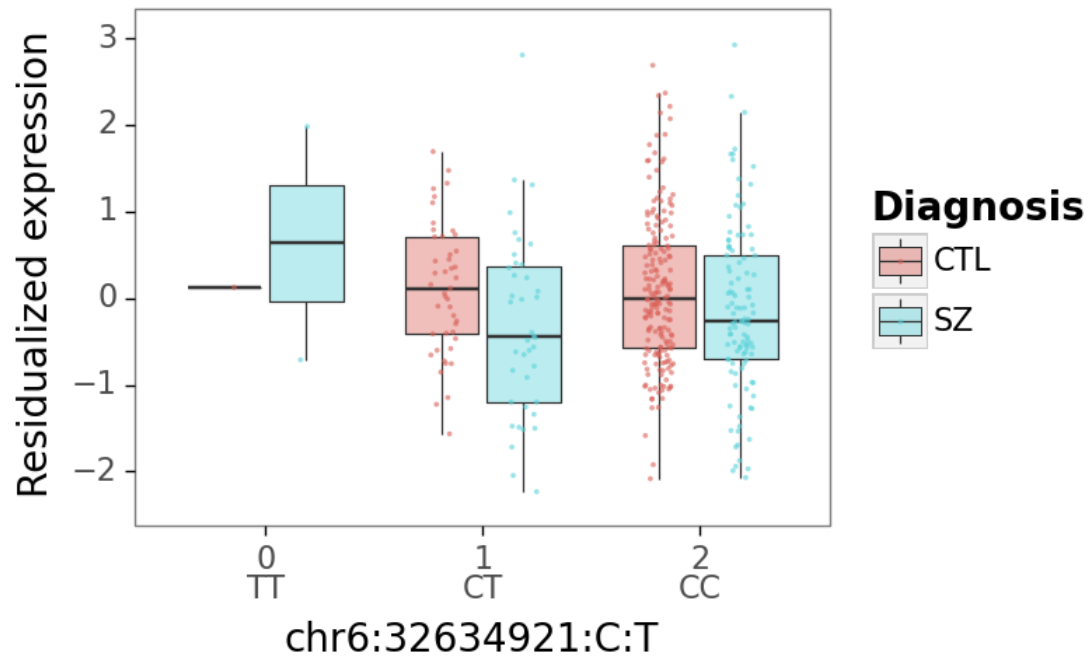
<ggplot: (8728655345273)>

FLOT1  
 ENSE00003656841.1  
 SZ GWAS pvalue: 4.4e-27  
 SZ risk allele: G  
 eQTL nominal p-value: 2.2e-04  
 DE adj.P.Val: 0.043



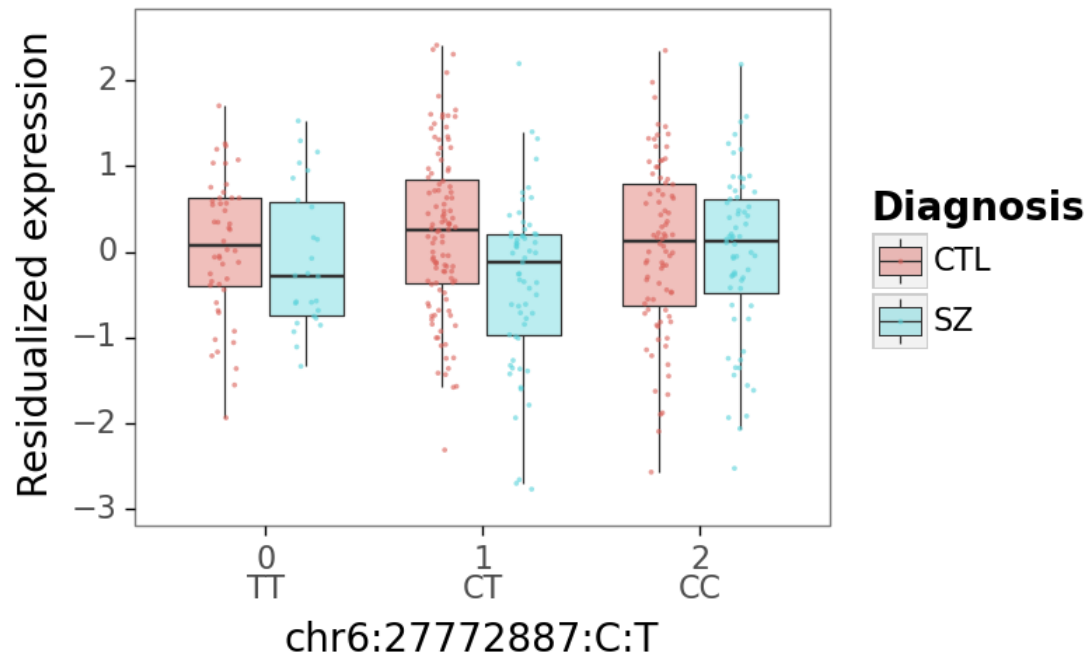
<ggplot: (8728674837279)>

BRD2  
 ENSE00003691002.1  
 SZ GWAS pvalue: 1.1e-22  
 SZ risk allele: C  
 eQTL nominal p-value: 1.8e-04  
 DE adj.P.Val: 0.046



<ggplot: (8728674192375)>

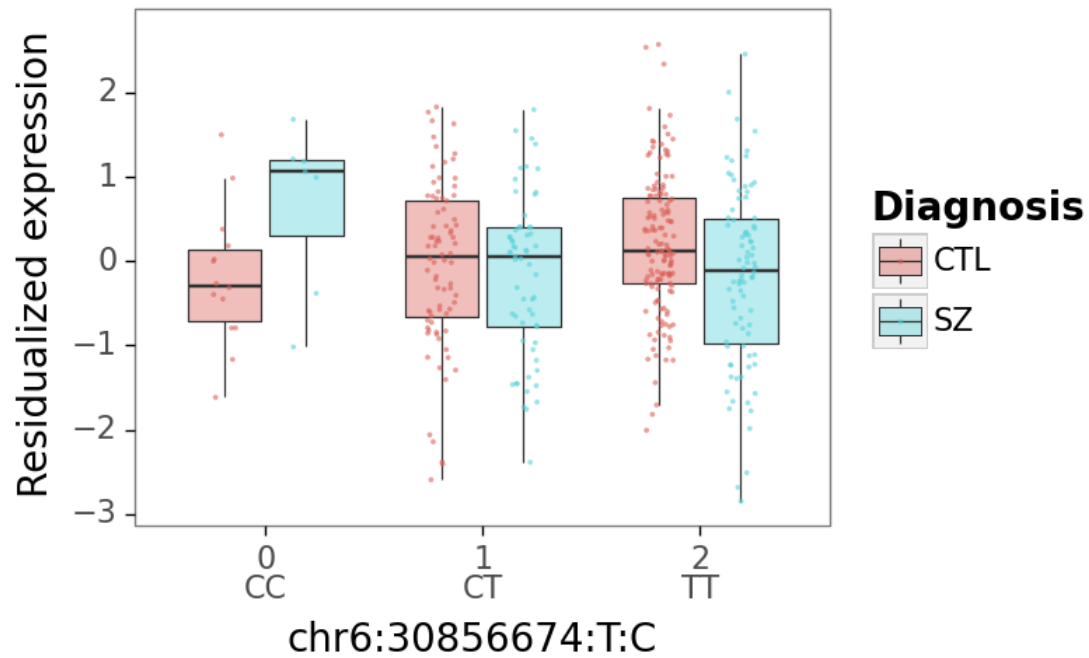
ZSCAN26  
 ENSE00001752123.3  
 SZ GWAS pvalue: 1.2e-18  
 SZ risk allele: C  
 eQTL nominal p-value: 4.9e-04  
 DE adj.P.Val: 0.019



<ggplot: (8728654507530)>

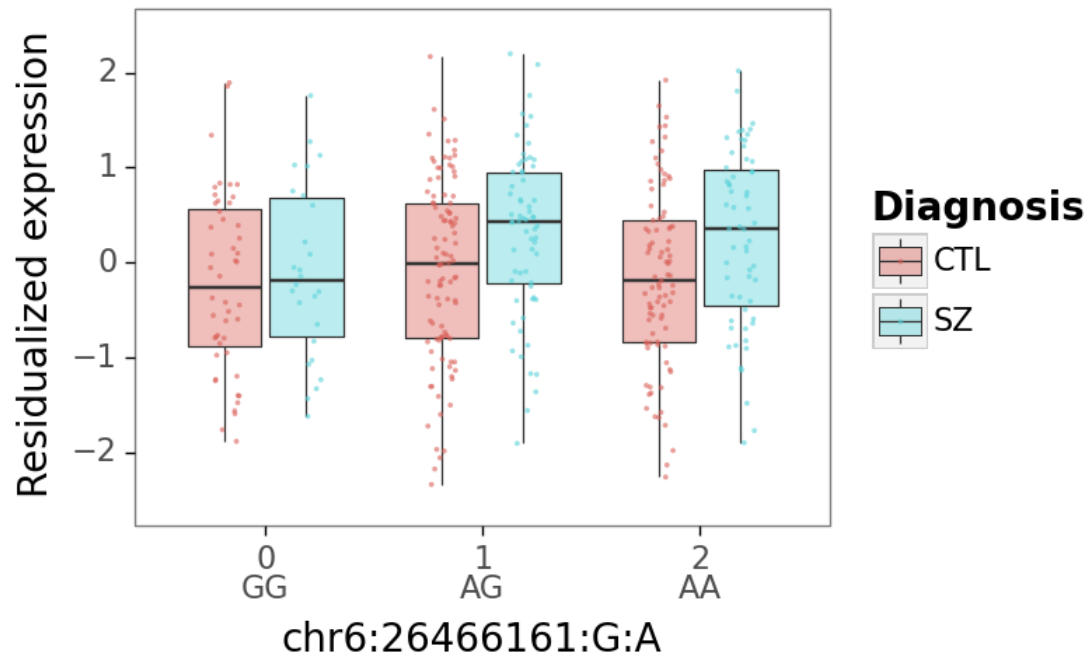


PPP1R10  
 ENSE00001919521.1  
 SZ GWAS pvalue: 2.3e-17  
 SZ risk allele: T  
 eQTL nominal p-value: 2.8e-04  
 DE adj.P.Val: 0.033



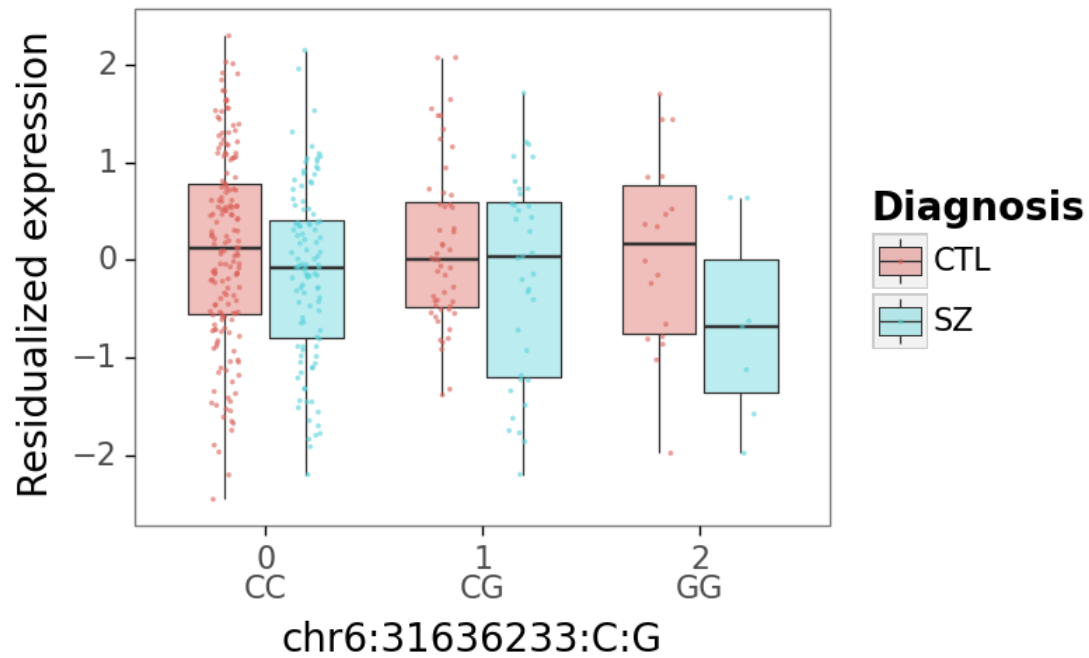
<ggplot: (8728653624037)>

HCG11  
 ENSE00001649663.2  
 SZ GWAS pvalue: 1.0e-14  
 SZ risk allele: A  
 eQTL nominal p-value: 2.9e-06  
 DE adj.P.Val: 0.001



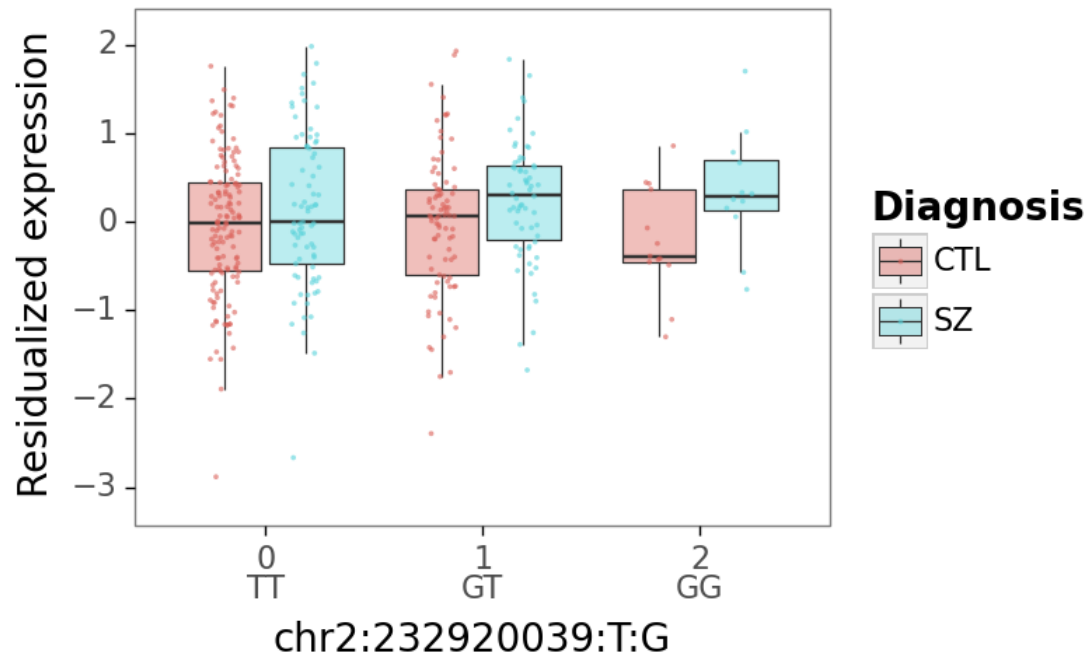
<ggplot: (8728653562489)>

ATF6B  
 ENSE00001919167.1  
 SZ GWAS pvalue: 1.6e-13  
 SZ risk allele: G  
 eQTL nominal p-value: 5.4e-05  
 DE adj.P.Val: 0.041



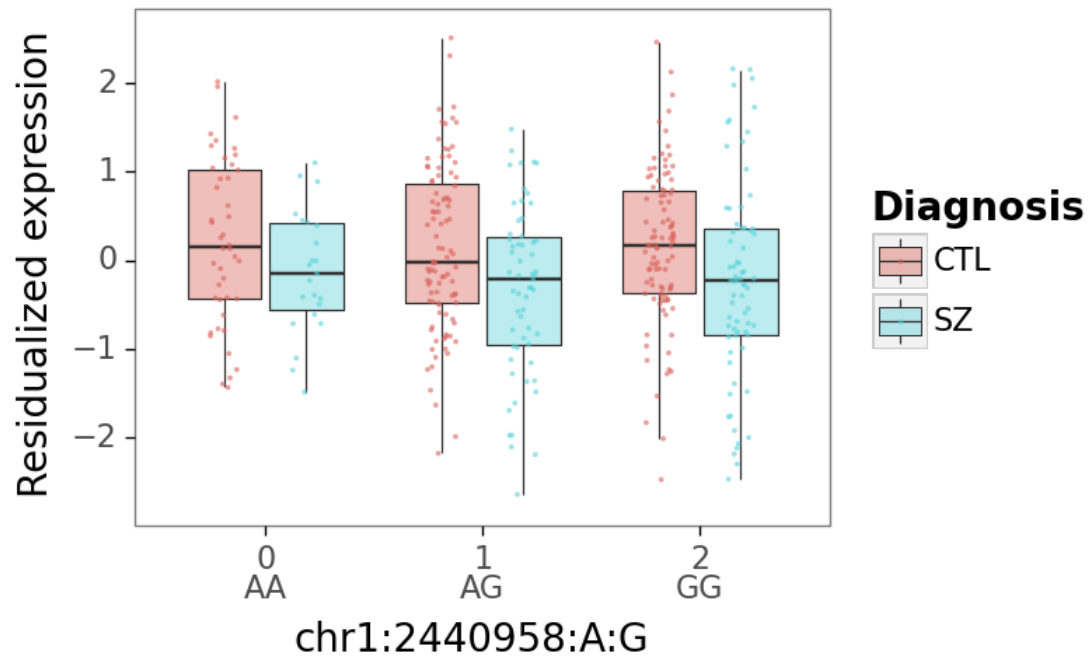
<ggplot: (8728655593975)>

NGEF  
 ENSE00001584949.1  
 SZ GWAS pvalue:  $2.0 \times 10^{-13}$   
 SZ risk allele: G  
 eQTL nominal p-value:  $3.2 \times 10^{-5}$   
 DE adj.P.Val: 0.039



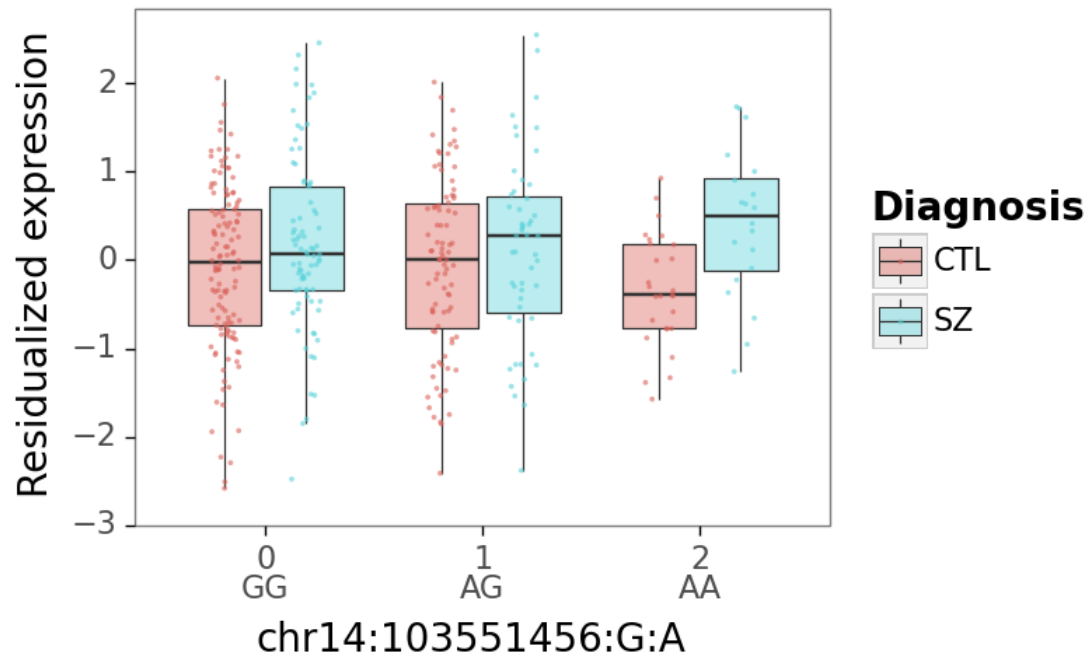
<ggplot: (8728655057399)>

PLCH2  
 ENSE00001701479.1  
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 SZ risk allele: G  
 eQTL nominal p-value: 2.1e-08  
 DE adj.P.Val: 0.002



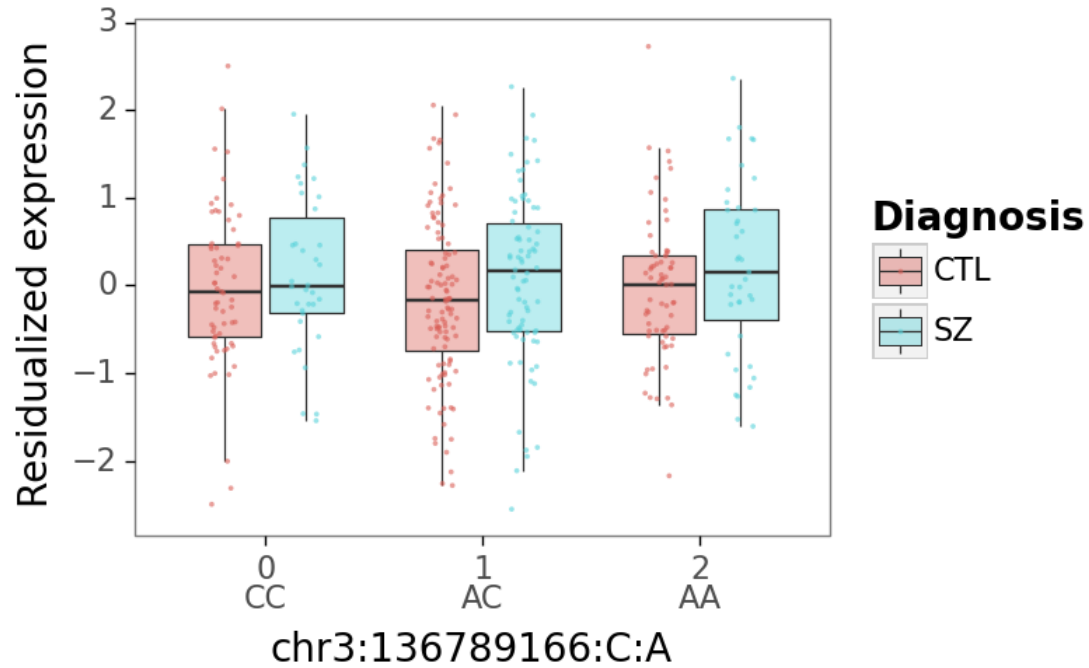
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AL049840.5  
 ENSE00003251427.1  
 SZ GWAS pvalue: 2.5e-10  
 SZ risk allele: A  
 eQTL nominal p-value: 2.2e-04  
 DE adj.P.Val: 0.043



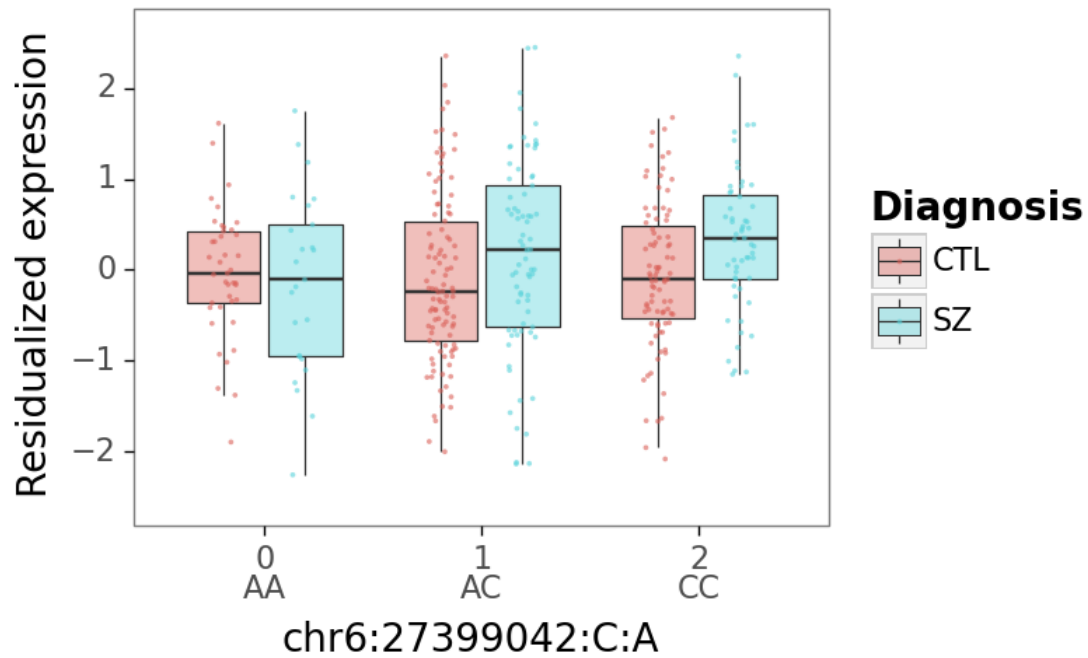
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SLC35G2  
 ENSE00001855416.1  
 SZ GWAS pvalue: 6.4e-10  
 SZ risk allele: A  
 eQTL nominal p-value: 2.4e-04  
 DE adj.P.Val: 0.018



<ggplot: (8728467964398)>

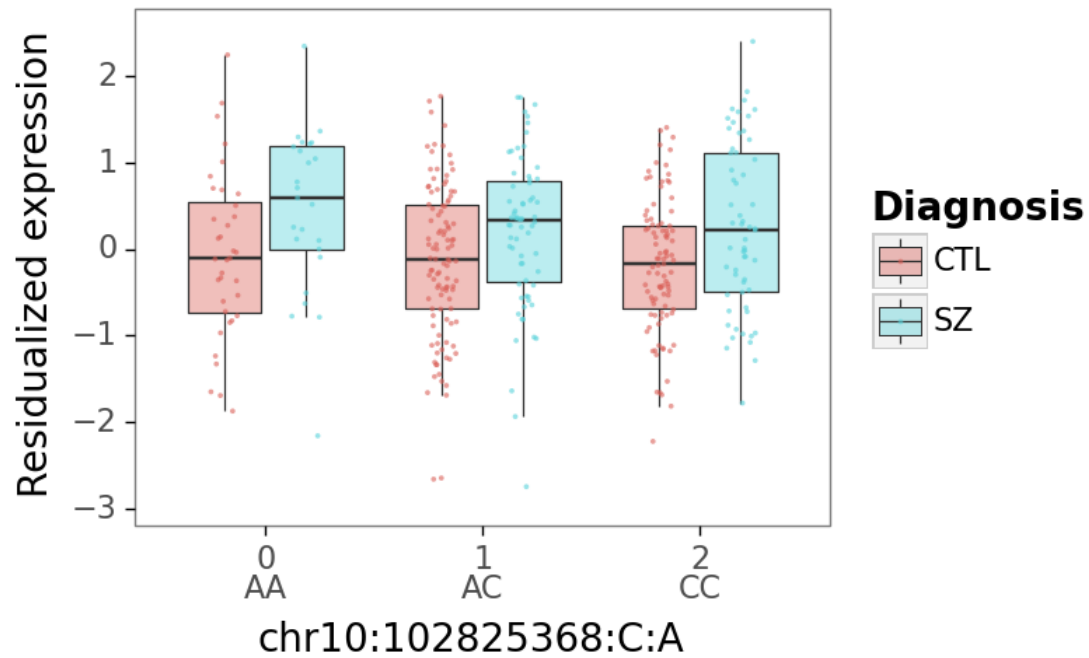
ZNF204P  
 ENSE00001700359.1  
 SZ GWAS pvalue: 6.5e-10  
 SZ risk allele: C  
 eQTL nominal p-value: 2.9e-04  
 DE adj.P.Val: 0.027



<ggplot: (8728467918318)>

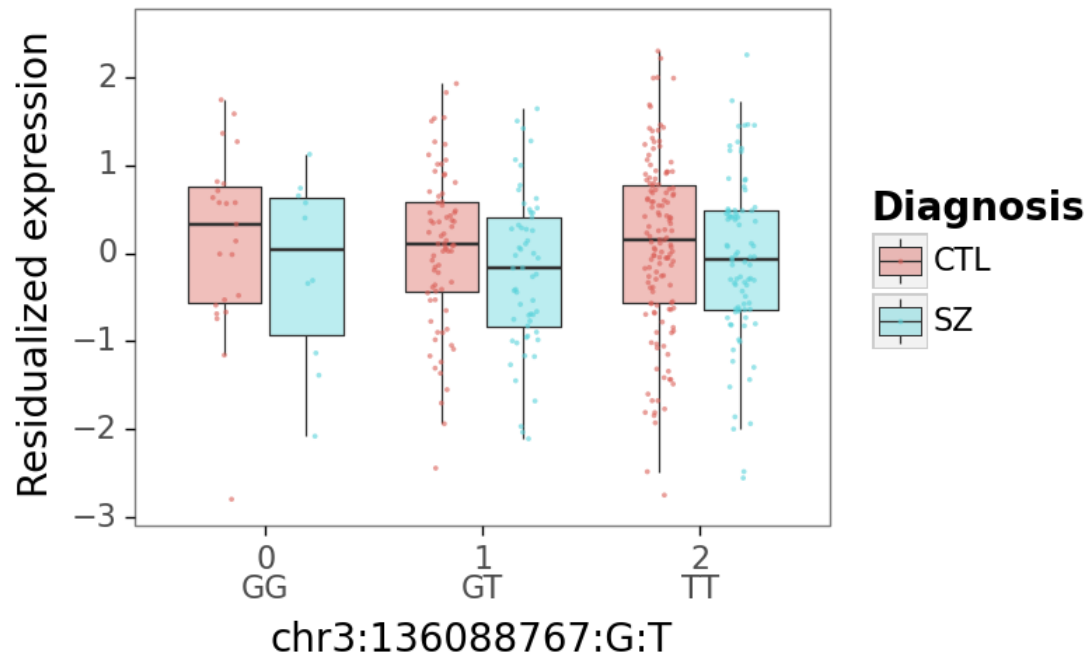


CNNM2  
ENSE00001288096.4  
SZ GWAS pvalue: 1.1e-09  
SZ risk allele: C  
eQTL nominal p-value: 1.3e-10  
DE adj.P.Val: 0.002



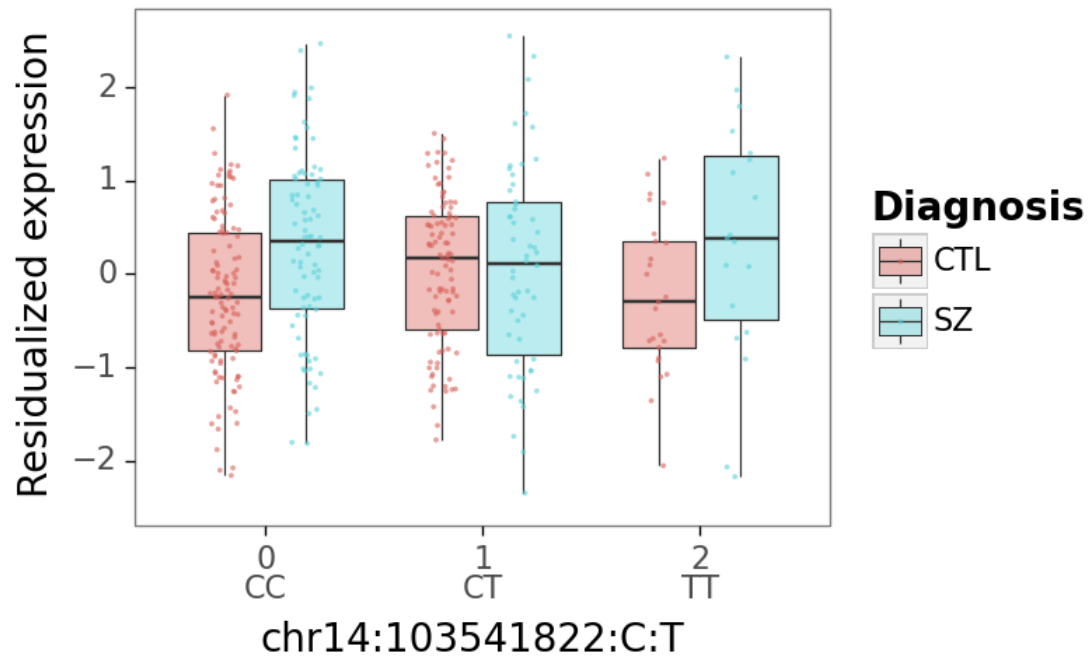
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PCCB  
 ENSE00001857296.1  
 SZ GWAS pvalue: 5.0e-09  
 SZ risk allele: T  
 eQTL nominal p-value: 2.8e-04  
 DE adj.P.Val: 0.046



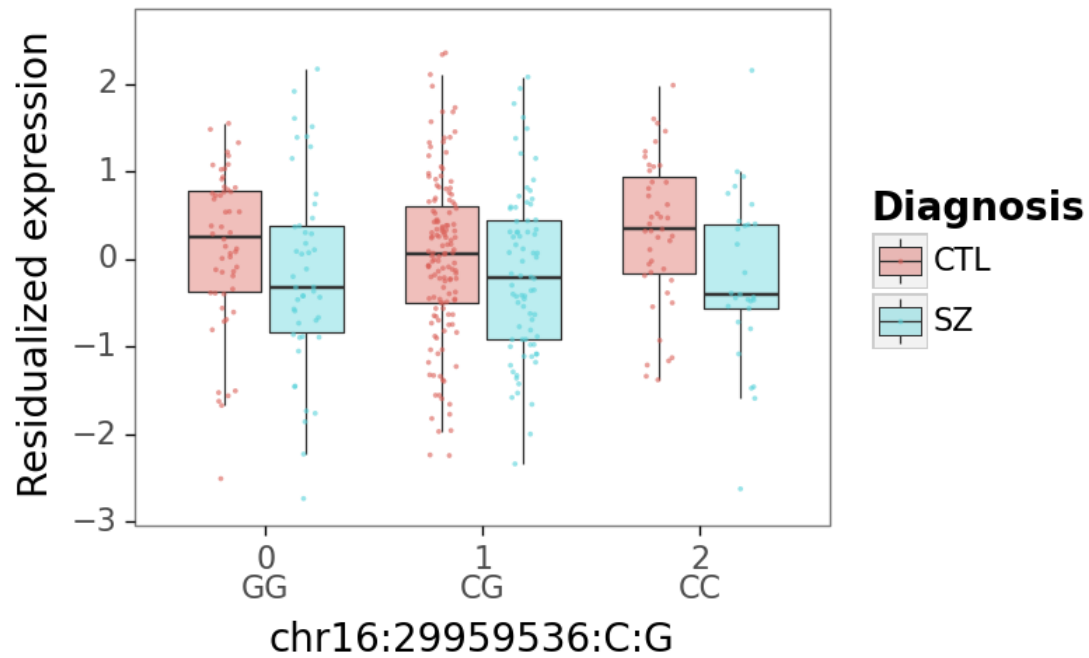
<ggplot: (8728653499895)>

ZFYVE21  
ENSE00003418764.1  
SZ GWAS pvalue: 6.9e-09  
SZ risk allele: T  
eQTL nominal p-value: 5.0e-05  
DE adj.P.Val: 0.001



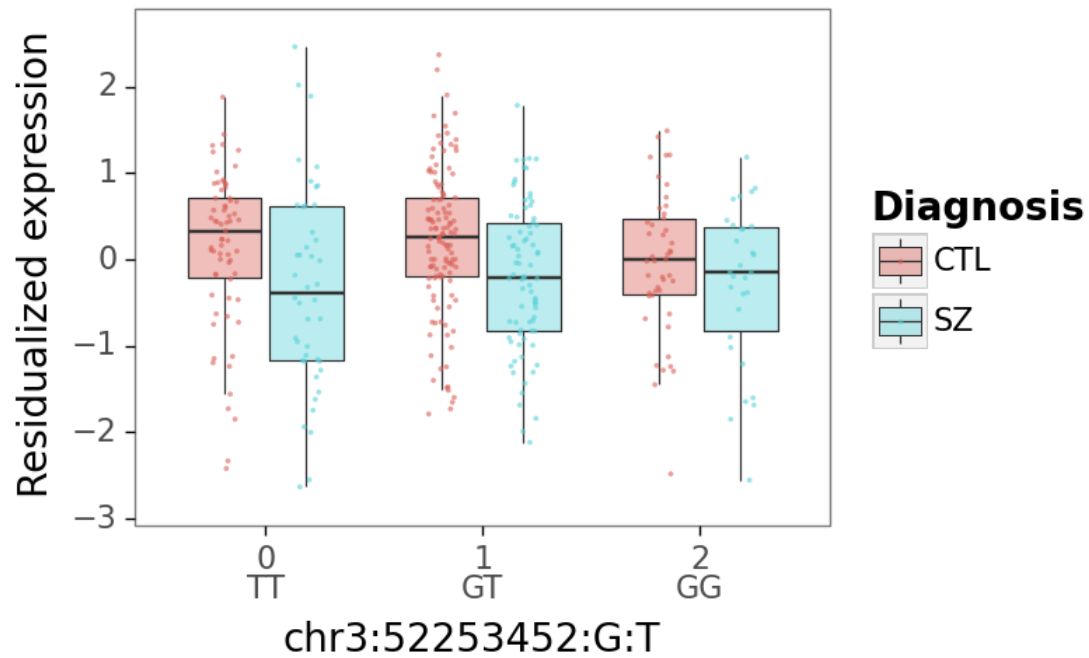
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HIRIP3  
 ENSE00002628577.2  
 SZ GWAS pvalue: 1.2e-08  
 SZ risk allele: C  
 eQTL nominal p-value: 5.9e-05  
 DE adj.P.Val: 0.019



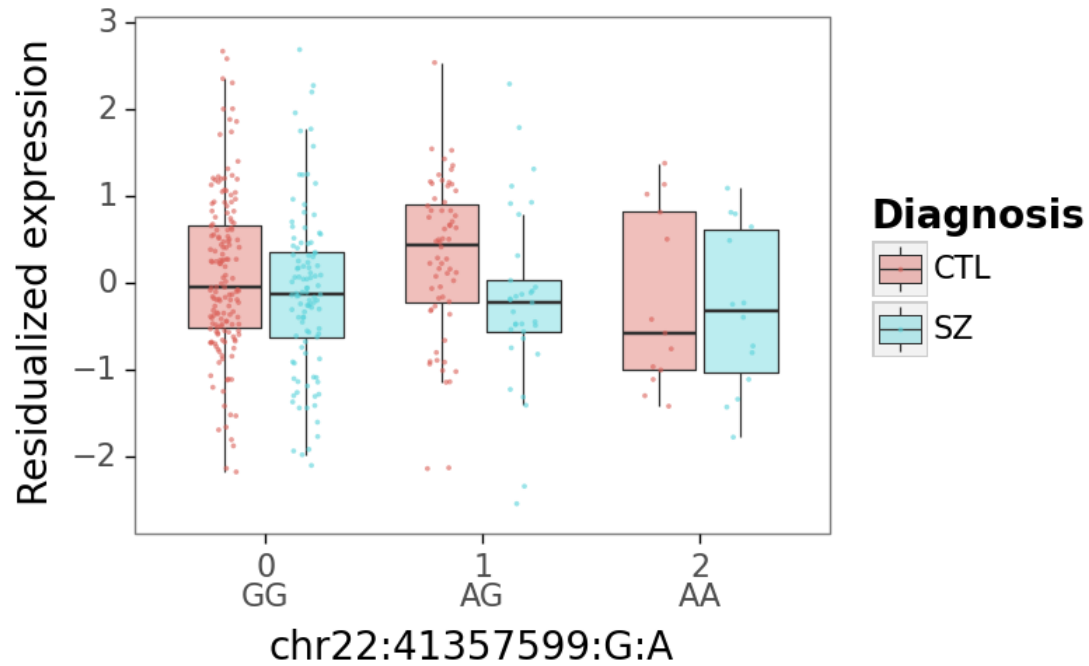
<ggplot: (8728675667800)>

PPM1M  
 ENSE00001578510.3  
 SZ GWAS pvalue: 1.4e-08  
 SZ risk allele: G  
 eQTL nominal p-value: 2.6e-04  
 DE adj.P.Val: 0.006



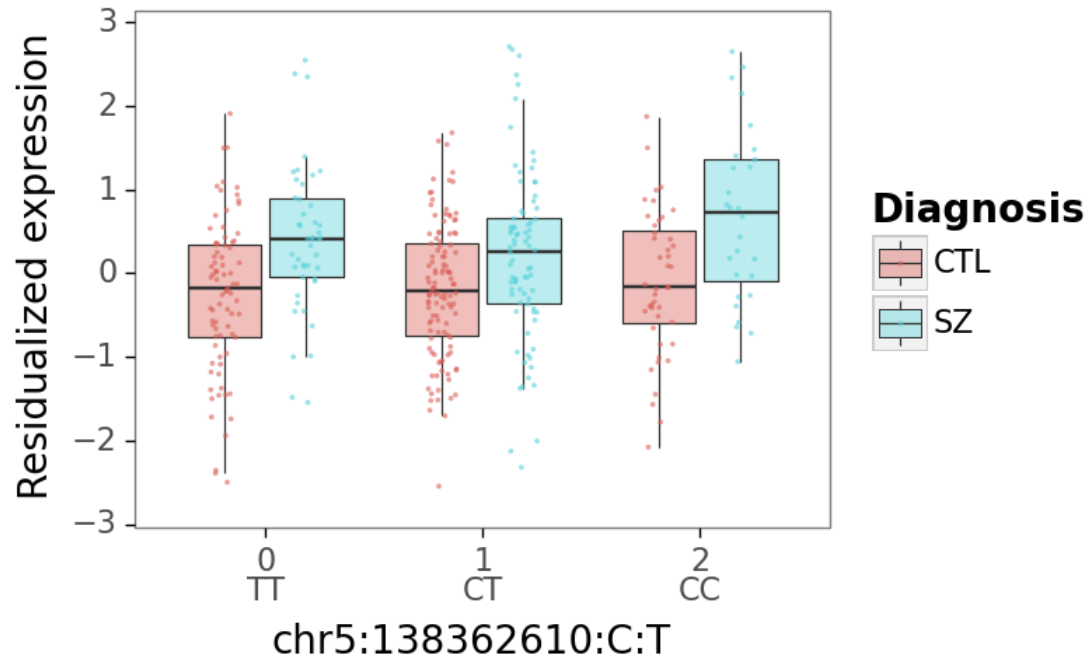
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ZC3H7B  
ENSE00000655656.1  
SZ GWAS pvalue: 1.8e-08  
SZ risk allele: A  
eQTL nominal p-value: 3.3e-05  
DE adj.P.Val: 0.025



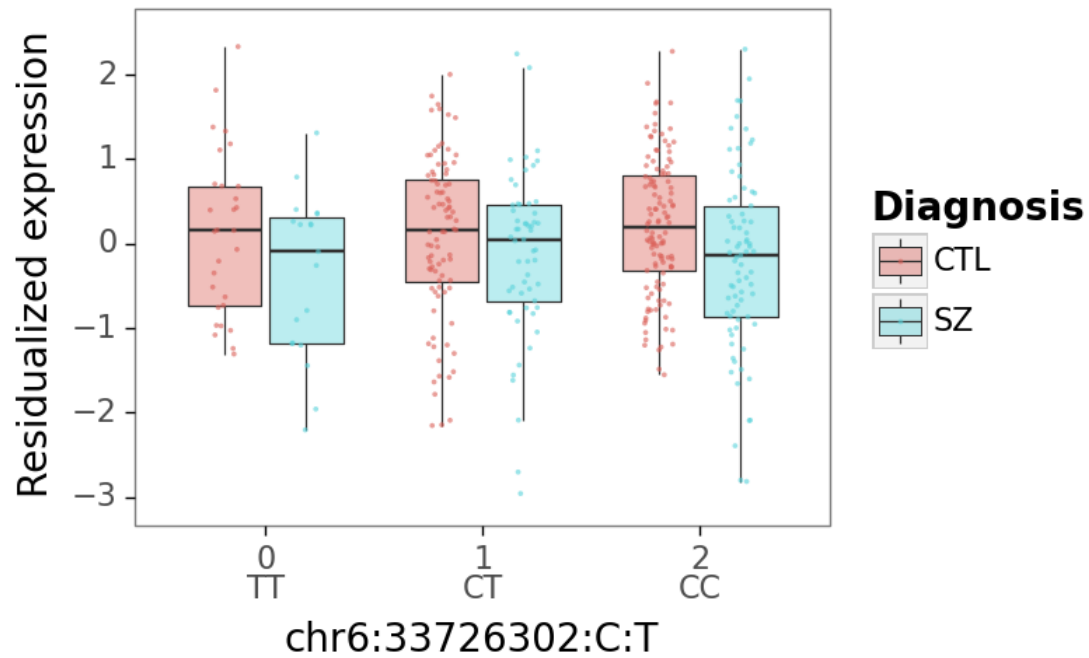
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REEP2  
 ENSE00001320042.5  
 SZ GWAS pvalue: 1.9e-08  
 SZ risk allele: C  
 eQTL nominal p-value: 2.3e-07  
 DE adj.P.Val: 0.000



<ggplot: (8728653678511)>

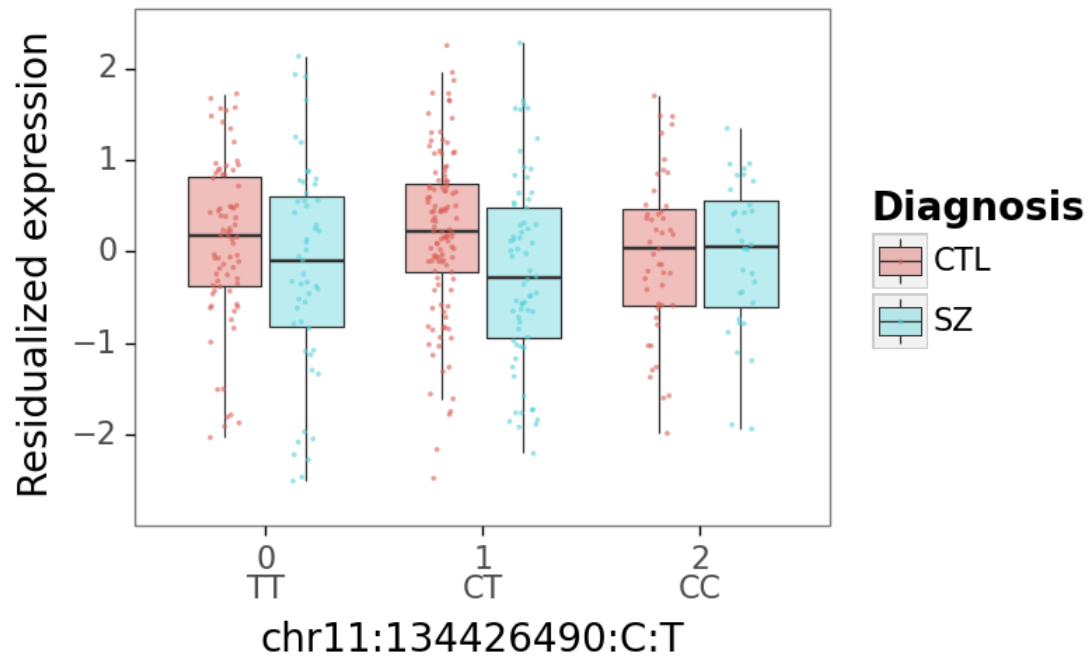
IP6K3  
 ENSE00001061200.1  
 SZ GWAS pvalue: 2.5e-08  
 SZ risk allele: C  
 eQTL nominal p-value: 5.0e-06  
 DE adj.P.Val: 0.025



<ggplot: (8728467744799)>

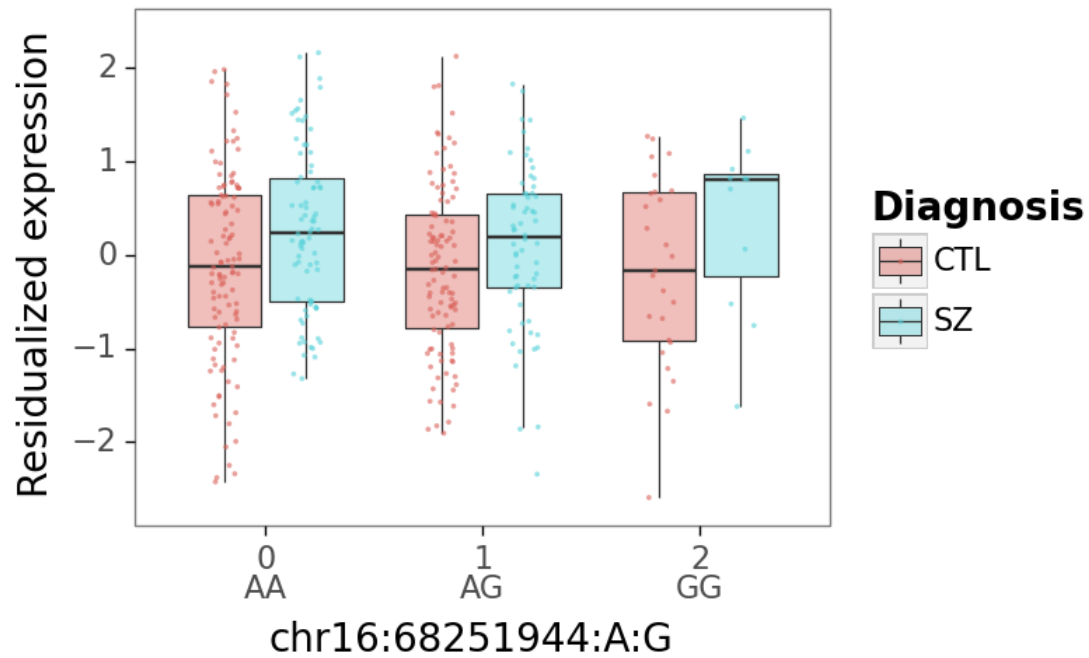


B3GAT1  
 ENSE00002197011.1  
 SZ GWAS pvalue: 3.0e-08  
 SZ risk allele: C  
 eQTL nominal p-value: 2.4e-05  
 DE adj.P.Val: 0.005



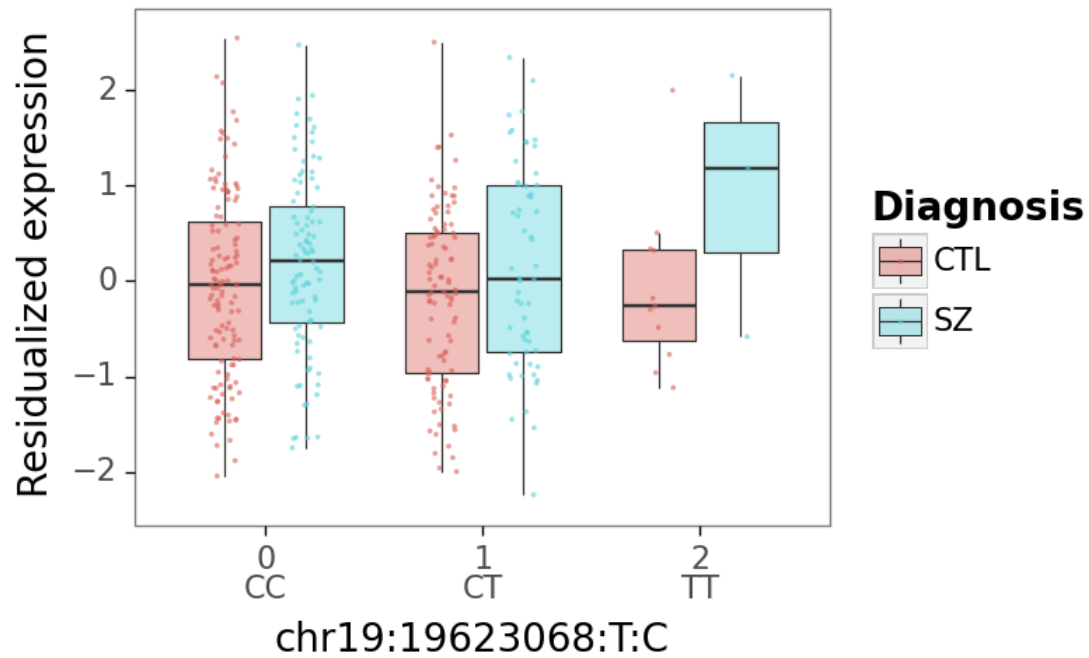
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SLC7A6  
ENSE00001616168.2  
SZ GWAS pvalue: 3.6e-08  
SZ risk allele: G  
eQTL nominal p-value: 1.3e-04  
DE adj.P.Val: 0.024



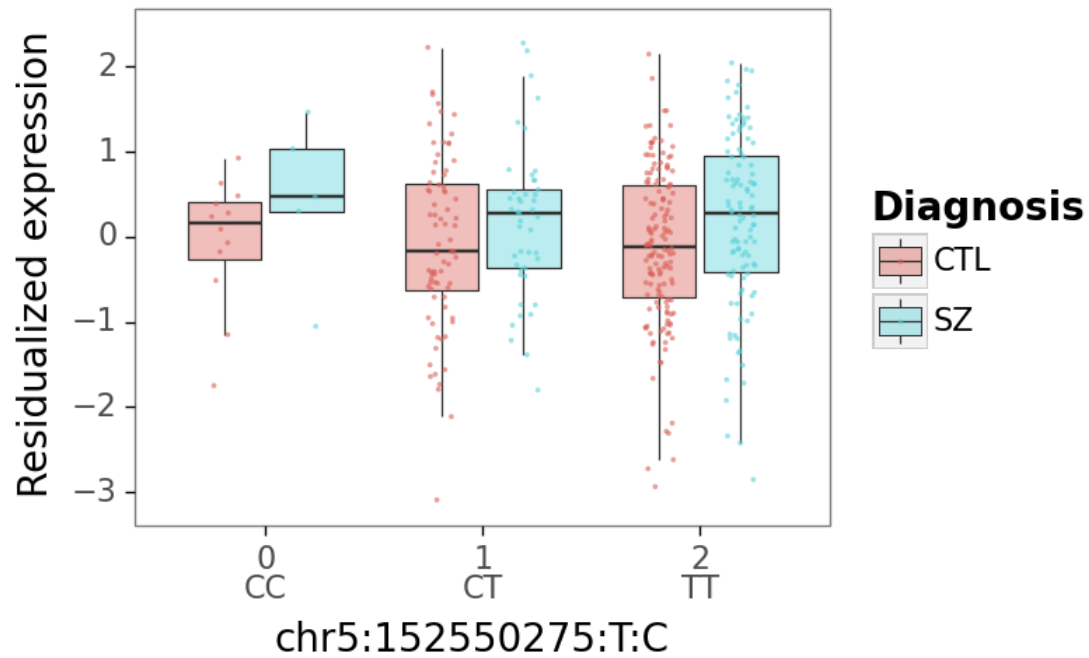
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ZNF14  
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SZ GWAS pvalue: 4.3e-08  
SZ risk allele: T  
eQTL nominal p-value: 1.0e-06  
DE adj.P.Val: 0.012



<ggplot: (8728468002925)>

LINC01470  
ENSE00002139369.1  
SZ GWAS pvalue: 4.5e-08  
SZ risk allele: T  
eQTL nominal p-value: 1.4e-11  
DE adj.P.Val: 0.007



<ggplot: (8728467626749)>