
title: "build_peak_EnPACT" author: "Saideep Gona" date: "2024-03-26" format: html:
code-fold: true code-summary: "Show the code" execute: freeze: true warning: false

Context

In this notebook, I build linearized Con-EnPACT models for peak data from Aracena et al.
The peak data are as follows:

ATAC - Chromatin Accessibility H3K27ac - Histone, Enhancers + TSS H3K27me3 -
Repression H3K4me1 - "Active" enhancers H3K4me3 - Enhancer

```
In [ ]: import os, sys
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import json

import subprocess

import pyliftover
```

```
In [ ]: # Set up modalities

path_to_config_template = "/beagle3/haky/users/saideep/github_repos/Con-EnPACT/
path_to_run_template = "/beagle3/haky/users/saideep/github_repos/Con-EnPACT/
path_to_project_dir = "/beagle3/haky/users/saideep/projects/Con_EnPACT/model
path_to_count_table = "/beagle3/haky/users/saideep/projects/aracena_modeling
path_to_annotations = "/beagle3/haky/users/saideep/projects/aracena_modeling

modality_pcs = {
    "H3K27ac":{
        "Flu":1,
        "NI":1
    },
    "H3K27me3":{
        "Flu":2,
        "NI":1
    },
    "H3K4me1":{
        "Flu":4,
        "NI":2
    },
    "H3K4me3":{
        "Flu":2,
        "NI":2
    },
    "ATAC":{
```

```

        "Flu":3,
        "NI":3
    }
}

```

Create Peak annotation files

```

In [ ]: def liftover_count_table(count_table, from_build="hg19", to_build="hg38", va

    # Liftover index of dataframe to new build, filter rows if not possible

    lo = pyliftover.LiftOver(from_build, to_build)

    new_regions = []
    new_regions_keep = []
    for region in count_table.index:
        chrom = region.split("_")[0]
        if len(region.split("_")) != 3:
            print("region length not 3")
            new_regions_keep.append(False)
            continue
        if chrom not in valid_chroms:
            print("chromosome not in valid chroms")
            new_regions_keep.append(False)
            continue
        start = int(region.split("_")[1])
        end = int(region.split("_")[2])

        new_start_coords = lo.convert_coordinate(chrom, start)
        if len(new_start_coords) == 0:
            print("No conversion")
            new_regions_keep.append(False)
            continue
        new_start = new_start_coords[0][1]

        new_end_coords = lo.convert_coordinate(chrom, end)
        if len(new_end_coords) == 0:
            print("No conversion")
            new_regions_keep.append(False)
            continue
        new_end = new_end_coords[0][1]

        new_regions.append(chrom + "_" + str(new_start) + "_" + str(new_end))
        new_regions_keep.append(True)

    new_count_table = count_table[new_regions_keep]
    new_count_table.index = new_regions
    return new_count_table

def liftover_predictdb_genotype_file(genotype_file, from_build="hg19", to_bu

    lo = pyliftover.LiftOver(from_build, to_build)

    genotypes_df = pd.read_csv(genotype_file, sep="\t")

```

```

chroms = genotypes_df["varID"].apply(lambda x: x.split("_")[0])
starts = genotypes_df["varID"].apply(lambda x: int(x.split("_")[1]))

refs = genotypes_df["varID"].apply(lambda x: x.split("_")[2])
alts = genotypes_df["varID"].apply(lambda x: x.split("_")[3])

new_starts = []

unconverted = 0

for chrom, start in zip(chroms, starts):
    new_coords = lo.convert_coordinate(chrom, start)
    if len(new_coords) == 0:
        unconverted += 1
        new_starts.append("UNCONVERTED")
    else:
        new_starts.append(new_coords[0][1])

if to_build == "hg19":
    build_tag = "b37"
    from_build_tag = "b38"
elif to_build == "hg38":
    build_tag = "b38"
    from_build_tag = "b37"

genotypes_df["varID"] = ["_".join([chrom, str(new_start), str(ref), str(alt)
genotypes_df_no_unconverted = genotypes_df[~genotypes_df["varID"].str.contains("UNCONVERTED")]
genotypes_df_no_unconverted = genotypes_df_no_unconverted.drop_duplicates()

print(genotypes_df.shape)
print(genotypes_df_no_unconverted.shape)

out_file = genotype_file.replace(from_build_tag, build_tag)
genotypes_df_no_unconverted.to_csv(out_file, sep="\t", index=False)
print("Unconverted: ", unconverted)

def liftover_snp_annotation_file(annotation_file, from_build="hg19", to_build="hg38"):
    lo = pyliftover.LiftOver(from_build, to_build)

    annotation_df = pd.read_csv(annotation_file, sep="\t")

    chroms = annotation_df["chr"].apply(lambda x: "chr"+str(x))
    starts = annotation_df["pos"].apply(lambda x: int(x))

    refs = annotation_df["ref_vcf"]
    alts = annotation_df["alt_vcf"]

    new_starts = []

```

```

unconverted = 0

for chrom, start in zip(chroms, starts):
    new_coords = lo.convert_coordinate(chrom, start)
    if len(new_coords) == 0:
        unconverted += 1
        new_starts.append("UNCONVERTED")
    else:
        new_starts.append(new_coords[0][1])

if to_build == "hg19":
    build_tag = "b37"
    from_build_tag = "b38"
elif to_build == "hg38":
    build_tag = "b38"
    from_build_tag = "b37"

varids = ["_".join([chrom, str(new_start), str(ref), str(alt), build_tag]) for chrom, new_start, ref, alt in zip(chroms, new_starts, ref, alt)]

annotation_df["varID"] = varids
annotation_df["rsid"] = varids

annotation_df["pos"] = new_starts

annotation_df_no_unconverted = annotation_df[~annotation_df["varID"].str.contains("UNCONVERTED")]

print(annotation_df.shape)
print(annotation_df_no_unconverted.shape)

out_file = annotation_file.replace(from_build_tag, build_tag)
annotation_df.to_csv(out_file, sep="\t", index=False)

print("Unconverted: ", unconverted)

def make_annotation_from_count(cur_counts, modality, annotation_dir, valid_c
    predictdb_annotation_file_dict = {
        "chr": [],
        "gene_id": [],
        "gene_name": [],
        "start": [],
        "end": [],
        "gene_type": []
    }

    annotation_file_dict = {"ensembl_gene_id": [],
                            "external_gene_name": [],
                            "chromosome_name": [],
                            "transcript_biotype": [],
                            "transcript_start": [],
                            "transcript_end": [],
                            "transcription_start_site": [],
                            "transcript_is_canonical": [],
                            "transcript_count": [],
                            "target_regions": []
    }

```

```

for row in cur_counts.iterrows():

    region = row[0]
    if len(region.split("_")) != 3:
        print("region length not 3")
        continue
    chrom = region.split("_")[0]
    if chrom not in valid_chroms:
        print("chromosome not in valid chroms")
        continue
    start = int(region.split("_")[1])
    end = int(region.split("_")[2])

    middle = (start + end) // 2

    predictdb_annotation_file_dict["chr"].append(chrom.strip("chr"))
    predictdb_annotation_file_dict["gene_id"].append(region)
    predictdb_annotation_file_dict["gene_name"].append(region)
    predictdb_annotation_file_dict["start"].append(start)
    predictdb_annotation_file_dict["end"].append(end)
    predictdb_annotation_file_dict["gene_type"].append("protein_coding")

    annotation_file_dict["ensembl_gene_id"].append(region)
    annotation_file_dict["external_gene_name"].append(region)

    annotation_file_dict["chromosome_name"].append(chrom.strip("chr"))
    annotation_file_dict["transcript_biotype"].append("NA")
    annotation_file_dict["transcript_start"].append(start)
    annotation_file_dict["transcript_end"].append(end)
    annotation_file_dict["transcription_start_site"].append(middle)
    annotation_file_dict["transcript_is_canonical"].append(1)
    annotation_file_dict["transcript_count"].append("NA")
    annotation_file_dict["target_regions"].append(region)

predictdb_annotation_file = pd.DataFrame(predictdb_annotation_file_dict)
print(predictdb_annotation_file.shape)
o_file = os.path.join(annotation_dir, f"{modality}_predictdb_annotation.
predictdb_annotation_file.to_csv(o_file, sep="\t", index=False)

annotation_file = pd.DataFrame(annotation_file_dict)
print(annotation_file.shape)
o_file = os.path.join(annotation_dir, f"{modality}_annotation.txt")
annotation_file.to_csv(o_file, sep=",", index=False)

```

Reformat normalized count tables, split Flu and NI and subset to genotype file

```

In [ ]: ## Reformat normalized count tables, split Flu and NI and subset to genotype

# genotype_file = "/beagle3/haky/users/saideep/projects/aracena_modeling/Inp
# genotype_data = pd.read_csv(genotype_file, sep="\t", index_col=0)

```

```

# genotype_data.head()
# genotype_samples = genotype_data.columns

# for modality in modality_pcs.keys():

#     cur_count_file = os.path.join(path_to_count_table, f"fully_preprocessed_{modality}.csv")
#     all_expression_ori = pd.read_csv(
#         cur_count_file,
#         sep=" ")

#     valid_chroms = "chr1,chr2,chr3,chr4,chr5,chr6,chr9,chr10,chr11,chr16,chr17,chr18,chr19,chr20,chr21,chr22,X,Y"
#     # Liftover peaks to hg38
#     all_expression = liftover_count_table(all_expression_ori, from_build="hg19", to_build="hg38")

#     # Make annotation file for EnPACT
#     make_annotation_from_count(all_expression, modality, path_to_annotation_file)

#     print(all_expression_ori.shape)
#     print(all_expression.shape)

#     # samples = all_expression.columns
#     samples = all_expression.columns

#     flu_samples = [x for x in samples if "Flu" in x]
#     ni_samples = [x for x in samples if "NI" in x]

#     flu_samples = [x for x in flu_samples if x.split("_")[0] in genotype_samples]
#     ni_samples = [x for x in ni_samples if x.split("_")[0] in genotype_samples]

#     flu_expression = all_expression[flu_samples]
#     ni_expression = all_expression[ni_samples]

#     flu_expression = flu_expression.rename(columns={x:x.replace("_Flu", "")})
#     ni_expression = ni_expression.rename(columns={x:x.replace("_NI", "")})

#     print(flu_expression.shape)
#     print(ni_expression.shape)

#     # Write reformed files

#     flu_expression.to_csv(cur_count_file.replace("preprocessed_", "preprocessed_flu_"))
#     ni_expression.to_csv(cur_count_file.replace("preprocessed_", "preprocessed_ni_"))

```

Liftover inputs for PredictDB

This isn't always necessary if your inputs are all already in the same genome build.

```

In [ ]: genotype_file_to_convert = "/beagle3/haky/users/saideep/projects/aracena_modelling/annotation_file_to_convert = "/beagle3/haky/users/saideep/projects/aracena_modelling/

```

```
converted_genotype_file = genotype_file_to_convert.replace("b37", "b38")
converted_annotation_file = annotation_file_to_convert.replace("b37", "b38")
```

```
In [ ]: # Convert genotype file to hg38 (shared among all runs)

# liftover_predicdb_genotype_file(genotype_file_to_convert, from_build="hg19")
```

```
In [ ]: # Convert SNP annotation file to hg38 (shared among all runs)

# liftover_snp_annotation_file(annotation_file_to_convert, from_build="hg19")
```

Train EnPACT models

```
In [ ]: window_sizes = [2,4,8,16,32,64,128]
```

```
In [ ]: for modality in modality_pcs.keys():
    for context in ["Flu", "NI"]:
        for window_size in window_sizes:
            cur_proj_dir = os.path.join(path_to_project_dir, context+"_"+modality)
            os.makedirs(cur_proj_dir, exist_ok=True)

            with open(path_to_config_template, "r") as f:

                config = json.load(f)
                config["general_parameters"]["project_directory"] = cur_proj_dir
                config["general_parameters"]["context"] = context

                config["generate_enpact_training_data"]["input_files"]["norm"]
                config["generate_enpact_training_data"]["reference_epigenome"]
                config["generate_enpact_training_data"]["input_files"]["gene"]

            with open(os.path.join(cur_proj_dir, "config.json"), "w") as f:
                json.dump(config, f, indent=4)

            with open(path_to_run_template, "r") as f:
                run = f.read()
                run = run.replace("CONFIG_FILE", os.path.join(cur_proj_dir, "c
                run = run.replace("JOBNAME", context+"_"+modality)
                run = run.replace("ERROR_LOG", os.path.join(cur_proj_dir, "er
                run = run.replace("OUTPUT_LOG", os.path.join(cur_proj_dir, "c
                with open(os.path.join(cur_proj_dir, "run_training.sbatch"), "
                    f.write(run)

            # subprocess.run(["sbatch",
            #                 os.path.join(cur_proj_dir, "run_training.sbatch
            #                 cwd=cur_proj_dir)
```

Personalized prediction evaluation

Before moving on to do linearization and TWAS, it is important to examine the raw personalized prediction performance of the EnPACT model. Also, based on analyzing the

window sizes during training, we can decide on the window size for personalized prediction and linearization. They are stored below:

```
In [ ]: optimal_window_sizes = {
    "H3K27ac":8,
    "H3K27me3":64,
    "H3K4me1":32,
    "H3K4me3":8,
    "ATAC":8
}

nfold_per_mode = {
    "H3K27ac":3,
    "H3K27me3":3,
    "H3K4me1":3,
    "H3K4me3":3,
    "ATAC":3
}

closest_enformer_track = {
    "H3K27ac":8,
    "H3K27me3":64,
    "H3K4me1":32,
    "H3K4me3":8,
    "ATAC":517
}

max_features = 500

path_to_pdb_standard_template = "/beagle3/haky/users/saideep/github_repos/Co
path_to_pp_template = "/beagle3/haky/users/saideep/github_repos/Con-EnPACT/r
```

Prepare VCF files for personalized prediction

Personalized prediction requires a VCF file encoding individual's genotypes. In this case, the existing VCF is in hg19 format, and the sample names are somewhat confusingly named relative to the other files. Liftover is not required as long as the other input files are in hg19 format, but it will help to rename the VCFs samples for consistency.

```
In [ ]: vcf_dir = "/beagle3/haky/users/saideep/projects/aracena_modeling/Inputs/VCF/

import glob
import cyvcf2

vcf_files = glob.glob(os.path.join(vcf_dir,"*.dose.vcf.gz.chr.vcf.gz.snps.vc
new_vcf_dir = "/beagle3/haky/users/saideep/projects/aracena_modeling/Inputs/
reheader_script_dir = "/beagle3/haky/users/saideep/github_repos/Daily-Blog-S
bcftools = "/beagle3/haky/users/saideep/software/bcftools-1.19/bcftools"

# with open(os.path.join(reheader_script_dir,"reheader.sh"), "w") as rs:
```



```
#     for vcf_file in vcf_files:

#         new_vcf_file = os.path.join(new_vcf_dir,os.path.basename(vcf_file))

#         cur_samples = cyvcf2.VCF(vcf_file).samples
#         new_samples = [x.split("_")[1] for x in cur_samples]

#         new_samples_file = os.path.join(reheader_script_dir,os.path.basename(new_vcf_file))
#         with open(new_samples_file, "w") as f:
#             f.write("\n".join(new_samples))

#         rs.write(f"{bcftools} reheader -s {new_samples_file} -o {new_vcf_file}")
#         rs.write(f"tabix -p vcf {new_vcf_file}\n\n")
```

Prepare config file for personalized prediction and run the relevant pipeline step

Personalized prediction requires running PredictDB training directly on the study population. This helps select features we will use for EnPACT personalized prediction as well as provide a model comparison. Therefore, the code below also generates the run script for standard predictDB. You should run that first, and then after the filtered db is created run the personalized prediction runsript.

```
In [ ]: for modality in modality_pcs.keys():
        for context in ["Flu","NI"]:
            cur_window_size = optimal_window_sizes[modality]
            cur_proj_dir = os.path.join(path_to_project_dir,context+"_"+modality)

            with open(os.path.join(cur_proj_dir,"config.json"),"r") as f:

                config = json.load(f)

                config["predictDB_standard"]["genotype_file"] = converted_genotype_file
                config["predictDB_standard"]["snp_annotation_file"] = converted_snp_annotation_file
                config["predictDB_standard"]["feature_annotation_file"] = os.path.join(cur_proj_dir,"feature_annotation.json")
                config["predictDB_standard"]["nfolds"] = nfolds_per_mode[modality]

                config["personalized_predictions"]["max_features"] = max_features
                config["personalized_predictions"]["path_to_epigenome_prediction"] = path_to_epigenome_prediction
                config["personalized_predictions"]["path_to_epigenome_config"] = path_to_epigenome_config
                config["personalized_predictions"]["path_to_vcf"] = new_vcf_dir
                config["personalized_predictions"]["epigenome_config_parameters"] = epigenome_config_parameters
                config["personalized_predictions"]["num_bins"] = optimal_window_size
                config["personalized_predictions"]["date"] = "04-16-2024"

                config["personalized_predictions"]["liftover"] = True
                config["personalized_predictions"]["liftover_target"] = "hg19"

            with open(os.path.join(cur_proj_dir,"config.json"),"w") as f:
                json.dump(config,f, indent=4)
```

```

with open(path_to_pdb_standard_template,"r") as f:
    run = f.read()
    run = run.replace("CONFIG_FILE",os.path.join(cur_proj_dir,"confi
    run = run.replace("JOBNAME",context+"_"+modality)
    run = run.replace("ERROR_LOG", os.path.join(cur_proj_dir,"error_
    run = run.replace("OUTPUT_LOG", os.path.join(cur_proj_dir,"outpu
    with open(os.path.join(cur_proj_dir,"run_predictdb_standard.sbat
        f.write(run)

with open(path_to_pp_template,"r") as f:
    run = f.read()
    run = run.replace("CONFIG_FILE",os.path.join(cur_proj_dir,"confi
    run = run.replace("JOBNAME",context+"_"+modality)
    run = run.replace("ERROR_LOG", os.path.join(cur_proj_dir,"error_
    run = run.replace("OUTPUT_LOG", os.path.join(cur_proj_dir,"outpu
    with open(os.path.join(cur_proj_dir,"run_personalized_prediction
        f.write(run)

# subprocess.run(["sbatch", os.path.join(cur_proj_dir,"run personali
# if modality != "ATAC":
#     if context == "Flu":
#         subprocess.run(["sbatch", os.path.join(cur_proj_dir,"inter
#                                     "run_predictDB_standard.sba
#                                     cwd=os.path.join(cur_proj_c

```

Linearize Peak EnPACT models

Unlike gene expression, peak data is relatively heterogenous. Different studies can have different sets of peaks, and the total number often greatly exceeds the number of genes. It makes sense, therefore, to have a selection process rather than trying to train PredictDB models for every peak available. In this case, since we are doing follow-up TWAS analysis, we can use GWAS loci to help us select peaks of interest.

We can start by examining a few GWAS summary stats and look for strong signals. These loci can be used as target sites for linearization since they are likely to have causal signal and are the places with potential to show up in downstream TWAS analysis.

Which GWAS to use?:

- Broad Allergy
- COVID GWAS
- Other infectious disease GWAS

GPU-hour costs for Enformer inference: 5hr per 20,000 sites

Set up loci selection

I am using Temi's repo: <https://github.com/hakyimlab/TFXcan-snakemake/tree/main>, which performs fine-mapping from GWAS summary stats, selects loci of interest, and then runs Enformer predictions for these regions. Once these personalized predictions are made, they can be used in all downstream EnPACT analyses.

EDIT: I've decided not to automate this here because it can be a pretty big pain to deal with.

```
In [ ]: # Dictionary to be added to config file
linearization_datasets = {
    "COVID":{
        "features":"/beagle3/haky/users/saideep/projects/aracena_modeling/SF
        "individuals":"/beagle3/haky/users/saideep/projects/enformer_all_geu
        "genotype_file":"/beagle3/haky/users/charles/project/singleXcanDL/Pr
        "snp_annotation_file":"/beagle3/haky/users/charles/project/singleXca
        "gene_annotation_file":"/beagle3/haky/users/saideep/projects/aracena
        "epigenome_pred_dir":"/beagle3/haky/users/saideep/projects/aracena_m
    }
}
```

```
In [ ]: path_to_linearization_template = "/beagle3/haky/users/saideep/github_repos/C

for modality in modality_pcs.keys():
    for context in ["Flu", "NI"]:
        cur_window_size = optimal_window_sizes[modality]
        cur_proj_dir = os.path.join(path_to_project_dir, context+"_"+modality

        with open(os.path.join(cur_proj_dir, "config.json"), "r") as f:

            config = json.load(f)
            config["linearization"]["linearization_datasets"] = linearizatio

        with open(os.path.join(cur_proj_dir, "config.json"), "w") as f:
            json.dump(config, f, indent=4)

        with open(path_to_linearization_template, "r") as f:
            run = f.read()
            run = run.replace("CONFIG_FILE", os.path.join(cur_proj_dir, "confi
            run = run.replace("JOBNAME", context+"_"+modality)
            run = run.replace("ERROR_LOG", os.path.join(cur_proj_dir, "error_
            run = run.replace("OUTPUT_LOG", os.path.join(cur_proj_dir, "outpu
            with open(os.path.join(cur_proj_dir, "run_linearization.sbatch"),
                f.write(run)

        subprocess.run(["sbatch", os.path.join(cur_proj_dir, "run_linearizati
```

```
sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
```

Submitted batch job 21726208

Submitted batch job 21726209

```
sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
```

Submitted batch job 21726210

Submitted batch job 21726211

Submitted batch job 21726212

```
sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
```

```

Submitted batch job 21726213
Submitted batch job 21726214
Submitted batch job 21726215
Submitted batch job 21726216
Submitted batch job 21726217

sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***

```

Run XWAS

Finally, we are ready to run XWAS analysis. Luckily, assuming all of the above have run successfully this should be a reasonable task.

```

In [ ]: # Dictionary to be added to config file
XWAS_datasets = {
    "COVID":{
        "GWAS_sum_stats":"/beagle3/haky/users/saideep/projects/aracena_model
        "linearization_dataset":"COVID"
    }
}

```

```

In [ ]: path_to_xwas_template = "/beagle3/haky/users/saideep/github_repos/Con-EnPACT

for modality in modality_pcs.keys():
    for context in ["Flu","NI"]:
        cur_window_size = optimal_window_sizes[modality]
        cur_proj_dir = os.path.join(path_to_project_dir,context+"_"+modality

        with open(os.path.join(cur_proj_dir,"config.json"),"r") as f:

            config = json.load(f)
            config["XWAS"]["XWAS_datasets"] = XWAS_datasets

        with open(os.path.join(cur_proj_dir,"config.json"),"w") as f:
            json.dump(config,f, indent=4)

        with open(path_to_xwas_template,"r") as f:
            run = f.read()
            run = run.replace("CONFIG_FILE",os.path.join(cur_proj_dir,"confi
            run = run.replace("JOBNAME",context+"_"+modality)
            run = run.replace("ERROR_LOG", os.path.join(cur_proj_dir,"error_
            run = run.replace("OUTPUT_LOG", os.path.join(cur_proj_dir,"outpu
            with open(os.path.join(cur_proj_dir,"run_xwas.sbatch"),"w") as f

```

```
f.write(run)
```

```
subprocess.run(["sbatch", os.path.join(cur_proj_dir, "run_xwas.sbatch")])
```

```
sbatch: Verify job submission ...  
sbatch: Using a shared partition ...  
sbatch: Partition: caslake  
sbatch: QOS-Flag: caslake  
sbatch: Account: pi-haky  
sbatch: Verification: ***PASSED***  
sbatch: Verify job submission ...  
sbatch: Using a shared partition ...  
sbatch: Partition: caslake  
sbatch: QOS-Flag: caslake  
sbatch: Account: pi-haky  
sbatch: Verification: ***PASSED***  
sbatch: Verify job submission ...  
sbatch: Using a shared partition ...  
sbatch: Partition: caslake  
sbatch: QOS-Flag: caslake  
sbatch: Account: pi-haky  
sbatch: Verification: ***PASSED***
```

Submitted batch job 21740221

Submitted batch job 21740222

Submitted batch job 21740223

```
sbatch: Verify job submission ...  
sbatch: Using a shared partition ...  
sbatch: Partition: caslake  
sbatch: QOS-Flag: caslake  
sbatch: Account: pi-haky  
sbatch: Verification: ***PASSED***  
sbatch: Verify job submission ...  
sbatch: Using a shared partition ...  
sbatch: Partition: caslake  
sbatch: QOS-Flag: caslake  
sbatch: Account: pi-haky  
sbatch: Verification: ***PASSED***  
sbatch: Verify job submission ...  
sbatch: Using a shared partition ...  
sbatch: Partition: caslake  
sbatch: QOS-Flag: caslake  
sbatch: Account: pi-haky  
sbatch: Verification: ***PASSED***
```

Submitted batch job 21740224

Submitted batch job 21740225

Submitted batch job 21740226

```

sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***
Submitted batch job 21740227
Submitted batch job 21740228
Submitted batch job 21740229
Submitted batch job 21740230

```

```

sbatch: Verify job submission ...
sbatch: Using a shared partition ...
sbatch: Partition: caslake
sbatch: QOS-Flag: caslake
sbatch: Account: pi-haky
sbatch: Verification: ***PASSED***

```

Let's also collect the XWAS results

```

In [ ]: results_tables = []

for modality in optimal_window_sizes.keys():
    for cond in ["Flu", "NI"]:

        for xd in XWAS_datasets.keys():

            cur_window_size = optimal_window_sizes[modality]

            cur_proj_dir = os.path.join(path_to_project_dir, cond+"_"+modality)
            path_to_results = os.path.join(cur_proj_dir, "intermediates", "XWAS")

            results = pd.read_csv(path_to_results, sep=",")
            results["modality"] = modality
            results["condition"] = cond
            results["GWAS_source"] = xd

            header=results.iloc[0]

            print(results.head())

            results_tables.append(results)

```

```
results_table_full = pd.concat(results_tables)
print(results_table_full.shape)

results_table_full.to_csv("/beagle3/haky/users/saideep/github_repos/Daily-BL
```


	gene	gene_name	zscore	\
0	chr3_45838989_45838991	chr3_45838989_45838991	-4.046273	
1	chr19_4719431_4719433	chr19_4719431_4719433	3.616343	
2	chr1_155203736_155203738	chr1_155203736_155203738	-3.470710	
3	chr12_112936943_112936945	chr12_112936943_112936945	3.347433	
4	chr9_133273813_133273815	chr9_133273813_133273815	3.083231	

	effect_size	pvalue	var_g	pred_perf_r2	pred_perf_pval	\
0	-12.541206	0.000052	0.000035	0.679051	4.986974e-140	
1	2.609658	0.000299	0.001313	0.742334	8.630024e-166	
2	-29.283244	0.000519	0.000006	0.757438	4.275992e-200	
3	3.680519	0.000816	0.000349	0.915979	0.000000e+00	
4	1.167531	0.002048	0.003344	0.993883	0.000000e+00	

	pred_perf_qval	n_snps_used	n_snps_in_cov	n_snps_in_model	modality	\
0	NaN	191	213	213	H3K27ac	
1	NaN	226	317	317	H3K27ac	
2	NaN	14	15	15	H3K27ac	
3	NaN	133	174	174	H3K27ac	
4	NaN	45	56	56	H3K27ac	

	condition	GWAS
0	Flu	COVID
1	Flu	COVID
2	Flu	COVID
3	Flu	COVID
4	Flu	COVID

	gene	gene_name	zscore	effect_size
0	chr3_45838989_45838991	chr3_45838989_45838991	-6.463302	-16.45281
1	chr17_49863303_49863305	chr17_49863303_49863305	-4.596455	-1.93195
2	chr21_33242905_33242907	chr21_33242905_33242907	-3.570149	-4.81877
3	chr9_133273813_133273815	chr9_133273813_133273815	3.549046	1.29734
4	chr19_50379362_50379364	chr19_50379362_50379364	3.024097	2.90513

	pvalue	var_g	pred_perf_r2	pred_perf_pval	pred_perf_qval	\
0	1.024422e-10	0.000062	0.710164	6.453670e-144	NaN	
1	4.297390e-06	0.002672	0.882065	0.000000e+00	NaN	
2	3.567786e-04	0.000196	0.772582	6.033189e-179	NaN	
3	3.866297e-04	0.003634	0.995342	0.000000e+00	NaN	
4	2.493761e-03	0.000384	0.854325	8.185288e-274	NaN	

	n_snps_used	n_snps_in_cov	n_snps_in_model	modality	condition	GWAS
0	154	162	162	H3K27ac	NI	COVID
1	136	160	160	H3K27ac	NI	COVID
2	167	187	187	H3K27ac	NI	COVID
3	70	74	74	H3K27ac	NI	COVID
4	97	128	128	H3K27ac	NI	COVID

	gene	gene_name	zscore	effect_size
0	chr6_31153455_31153457	chr6_31153455_31153457	-3.686652	-1.041724

1	chr17_49863303_49863305	chr17_49863303_49863305	-3.314173	-3.383596
2	chr19_4719431_4719433	chr19_4719431_4719433	-3.077552	-1.828643
3	chr19_48867352_48867354	chr19_48867352_48867354	-2.821971	-2.351931
4	chr3_45838989_45838991	chr3_45838989_45838991	2.700055	1.143763

	pvalue	var_g	pred_perf_r2	pred_perf_pval	pred_perf_qval	\
0	0.000227	0.004325	0.989233	0.000000e+00		NaN
1	0.000919	0.000471	0.865508	4.692603e-262		NaN
2	0.002087	0.000904	0.902207	0.000000e+00		NaN
3	0.004773	0.000683	0.898959	0.000000e+00		NaN
4	0.006933	0.001806	0.893569	0.000000e+00		NaN

	n_snps_used	n_snps_in_cov	n_snps_in_model	modality	condition	GWAS
0	127	138	138	H3K27me3	Flu	COVID
1	158	190	190	H3K27me3	Flu	COVID
2	102	152	152	H3K27me3	Flu	COVID
3	119	165	165	H3K27me3	Flu	COVID
4	115	126	126	H3K27me3	Flu	COVID

	gene	gene_name	zscore	\
0	chr19_4719431_4719433	chr19_4719431_4719433	-4.186584	
1	chr6_31153455_31153457	chr6_31153455_31153457	-3.738601	
2	chr17_49863303_49863305	chr17_49863303_49863305	-2.978499	
3	chr12_112936943_112936945	chr12_112936943_112936945	2.758486	
4	chr3_45838989_45838991	chr3_45838989_45838991	2.684772	

	effect_size	pvalue	var_g	pred_perf_r2	pred_perf_pval	\
0	-2.311632	0.000028	0.001086	0.893918	0.000000e+00	
1	-1.018564	0.000185	0.004601	0.989930	0.000000e+00	
2	-3.028647	0.002897	0.000472	0.870368	2.503403e-267	
3	6.500054	0.005807	0.000068	0.835311	2.062655e-226	
4	1.130361	0.007258	0.001833	0.902027	0.000000e+00	

	pred_perf_qval	n_snps_used	n_snps_in_cov	n_snps_in_model	modality	\
0	NaN	161	228	228	H3K27me3	
1	NaN	123	132	132	H3K27me3	
2	NaN	175	208	208	H3K27me3	
3	NaN	153	186	186	H3K27me3	
4	NaN	120	131	131	H3K27me3	

	condition	GWAS
0	NI	COVID
1	NI	COVID
2	NI	COVID
3	NI	COVID
4	NI	COVID

	gene	gene_name	zscore	effect_size
0	chr19_4719431_4719433	chr19_4719431_4719433	7.166042	5.19273
1	chr21_33242905_33242907	chr21_33242905_33242907	-6.021281	-4.21204
2	chr17_49863303_49863305	chr17_49863303_49863305	-5.044558	-4.01721
3	chr9_133273813_133273815	chr9_133273813_133273815	4.082147	1.98663
4	chr6_31153455_31153457	chr6_31153455_31153457	4.068298	1.30432

8

	pvalue	var_g	pred_perf_r2	pred_perf_pval	pred_perf_qval	\
0	7.719687e-13	0.000858	0.742689	6.624718e-166	NaN	
1	1.730420e-09	0.000650	0.917593	0.000000e+00	NaN	
2	4.545710e-07	0.000746	0.787245	0.000000e+00	NaN	
3	4.462149e-05	0.002065	0.993723	0.000000e+00	NaN	
4	4.735777e-05	0.003252	0.981365	0.000000e+00	NaN	

	n_snps_used	n_snps_in_cov	n_snps_in_model	modality	condition	GWAS
0	131	193	193	H3K4me1	Flu	COVID
1	139	162	162	H3K4me1	Flu	COVID
2	131	163	163	H3K4me1	Flu	COVID
3	66	83	83	H3K4me1	Flu	COVID
4	174	192	192	H3K4me1	Flu	COVID

	gene	gene_name	zscore	effect_size
0	chr19_4719431_4719433	chr19_4719431_4719433	6.871495	5.05601
1	chr21_33242905_33242907	chr21_33242905_33242907	-5.683134	-4.02402
2	chr17_49863303_49863305	chr17_49863303_49863305	-4.940898	-3.61424
3	chr6_31153455_31153457	chr6_31153455_31153457	4.062374	1.26317
4	chr9_133273813_133273815	chr9_133273813_133273815	3.940389	1.82773

	pvalue	var_g	pred_perf_r2	pred_perf_pval	pred_perf_qval	\
0	6.353239e-12	0.000833	0.697355	1.105875e-150	NaN	
1	1.322482e-08	0.000652	0.918320	0.000000e+00	NaN	
2	7.776357e-07	0.000882	0.890964	0.000000e+00	NaN	
3	4.857627e-05	0.003434	0.978835	0.000000e+00	NaN	
4	8.134961e-05	0.002284	0.994095	0.000000e+00	NaN	

	n_snps_used	n_snps_in_cov	n_snps_in_model	modality	condition	GWAS
0	156	225	225	H3K4me1	NI	COVID
1	171	195	195	H3K4me1	NI	COVID
2	108	134	134	H3K4me1	NI	COVID
3	162	177	177	H3K4me1	NI	COVID
4	44	60	60	H3K4me1	NI	COVID

	gene	gene_name	zscore	\
0	chr21_33242905_33242907	chr21_33242905_33242907	-6.554030	
1	chr12_112936943_112936945	chr12_112936943_112936945	6.393212	
2	chr17_49863303_49863305	chr17_49863303_49863305	4.900311	
3	chr19_50379362_50379364	chr19_50379362_50379364	4.222593	
4	chr19_4719431_4719433	chr19_4719431_4719433	4.037497	

	effect_size	pvalue	var_g	pred_perf_r2	pred_perf_pval	\
0	-6.260170	5.600477e-11	0.000413	0.879327	1.692943e-283	
1	4.881488	1.624368e-10	0.000647	0.974020	0.000000e+00	
2	1.507517	9.568527e-07	0.004953	0.933669	0.000000e+00	
3	3.417448	2.415081e-05	0.000501	0.953136	0.000000e+00	
4	3.229335	5.402464e-05	0.000879	0.738895	1.763889e-158	

	pred_perf_qval	n_snps_used	n_snps_in_cov	n_snps_in_model	modality	\
--	----------------	-------------	---------------	-----------------	----------	---

0	NaN	205	244	244	H3K4me3
1	NaN	84	102	102	H3K4me3
2	NaN	91	101	101	H3K4me3
3	NaN	54	66	66	H3K4me3
4	NaN	149	220	220	H3K4me3

	condition	GWAS
0	Flu	COVID
1	Flu	COVID
2	Flu	COVID
3	Flu	COVID
4	Flu	COVID

	gene	gene_name	zscore	\
0	chr21_33242905_33242907	chr21_33242905_33242907	-7.217360	
1	chr12_112936943_112936945	chr12_112936943_112936945	5.867753	
2	chr17_49863303_49863305	chr17_49863303_49863305	4.460480	
3	chr9_133273813_133273815	chr9_133273813_133273815	4.048731	
4	chr19_50379362_50379364	chr19_50379362_50379364	3.871139	

	effect_size	pvalue	var_g	pred_perf_r2	pred_perf_pval	\
0	-6.778290	5.300657e-13	0.000445	0.875814	1.098475e-276	
1	5.788117	4.417404e-09	0.000384	0.912724	0.000000e+00	
2	3.788385	8.177643e-06	0.000671	0.890077	0.000000e+00	
3	3.623972	5.149614e-05	0.000568	0.963383	0.000000e+00	
4	3.475773	1.083280e-04	0.000425	0.935749	0.000000e+00	

	pred_perf_qval	n_snps_used	n_snps_in_cov	n_snps_in_model	modality	\
0	NaN	137	159	159	H3K4me3	
1	NaN	172	227	227	H3K4me3	
2	NaN	102	117	117	H3K4me3	
3	NaN	145	178	178	H3K4me3	
4	NaN	93	120	120	H3K4me3	

	condition	GWAS
0	NI	COVID
1	NI	COVID
2	NI	COVID
3	NI	COVID
4	NI	COVID

	gene	gene_name	zscore	effect_size
0	chr21_33242905_33242907	chr21_33242905_33242907	-5.589137	-6.95990
1	chr19_4719431_4719433	chr19_4719431_4719433	5.080926	12.28892
2	chr17_49863303_49863305	chr17_49863303_49863305	-4.737094	-3.25776
3	chr9_133273813_133273815	chr9_133273813_133273815	3.925288	2.30850
4	chr19_50379362_50379364	chr19_50379362_50379364	2.589867	2.19456

	pvalue	var_g	pred_perf_r2	pred_perf_pval	pred_perf_qval	\
0	2.282012e-08	0.000218	0.852828	1.751426e-251	NaN	
1	3.755987e-07	0.000101	0.511263	8.683987e-80	NaN	
2	2.168046e-06	0.000995	0.911933	0.000000e+00	NaN	

3	8.662607e-05	0.001287	0.996425	0.000000e+00	NaN
4	9.601297e-03	0.000431	0.950349	0.000000e+00	NaN

	n_snps_used	n_snps_in_cov	n_snps_in_model	modality	condition	GWAS
0	138	158	158	ATAC	Flu	COVID
1	90	138	138	ATAC	Flu	COVID
2	74	93	93	ATAC	Flu	COVID
3	52	60	60	ATAC	Flu	COVID
4	107	139	139	ATAC	Flu	COVID

	gene	gene_name	zscore	effect_size
e \				
0	chr17_49863303_49863305	chr17_49863303_49863305	-4.878925	-2.39873
4				
1	chr21_33242905_33242907	chr21_33242905_33242907	-4.070918	-5.62426
0				
2	chr9_133273813_133273815	chr9_133273813_133273815	3.819061	3.07464
4				
3	chr19_4719431_4719433	chr19_4719431_4719433	-3.488570	-7.91230
8				
4	chr3_45838989_45838991	chr3_45838989_45838991	-3.384359	-7.73003
9				

	pvalue	var_g	pred_perf_r2	pred_perf_pval	pred_perf_qval	\
0	0.000001	0.001937	0.920091	0.000000e+00	NaN	
1	0.000047	0.000179	0.826215	1.277127e-227	NaN	
2	0.000134	0.000689	0.992612	0.000000e+00	NaN	
3	0.000486	0.000033	0.501268	2.060973e-77	NaN	
4	0.000713	0.000069	0.800622	1.797418e-213	NaN	

	n_snps_used	n_snps_in_cov	n_snps_in_model	modality	condition	GWAS
0	82	104	104	ATAC	NI	COVID
1	127	143	143	ATAC	NI	COVID
2	58	78	78	ATAC	NI	COVID
3	80	112	112	ATAC	NI	COVID
4	153	167	167	ATAC	NI	COVID

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