

The Multi-State Epigenetic Pacemaker enables the identification of combinations of factors that influence DNA methylation

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Abstract

Epigenetic clocks, DNA methylation based predictive models of chronological age, are often utilized to study aging associated biology. Despite their widespread use, these methods do not account for other factors that also contribute to the variability of DNA methylation data. For example, many CpG sites show strong sex-specific or cell type specific patterns that likely impact the predictions of epigenetic age. To overcome these limitations, we developed a multidimensional extension of the Epigenetic Pacemaker, the Multi-State Epigenetic Pacemaker (MSEPM). We show that the MSEPM is capable of accurately modeling multiple methylation associated factors simultaneously, while also providing site specific models that describe the per site relationship between methylation and these factors. We utilized the MSEPM with a large aggregate cohort of blood methylation data to construct models of the effects of age, sex and cell type heterogeneity on DNA methylation. We found that these models capture a large fraction of the variability at thousands of DNA methylation sites. Moreover, this approach allows us to identify sites that are primarily affected by aging and no other factors. An analysis of these sites reveals that those that lose methylation over time are enriched for CTCF transcription factor chip peaks, while those that gain methylation over time are associated with bivalent promoters of genes that are not expressed in blood. These observations suggest mechanisms that underlie age associated methylation changes and suggest that age associated increases in methylation may not have strong functional consequences on cell states. In conclusion, the MSEPM is capable of accurately modeling multiple methylation associated factors and the models produced can illuminate site specific combinations of factors that affect methylation dynamics.

1 Introduction

DNA methylation, the addition of a methyl group to the fifth carbon of the cytosine pyrimidine ring, is associated with the topological organization of the cellular genome, gene expression and the state of a cell. Within a population of cells the methylation pattern at certain sites can change

34 predictably with the age of the individual from which the cells are drawn.
35 This predictable nature of DNA methylation has led to the development
36 of accurate DNA methylation based predictive models for age and health,
37 termed epigenetic clocks. The difference between the predicted and the
38 expected epigenetic age given an individual's chronological age has been
39 interpreted as a measure of age acceleration[1], and has been associated
40 with mortality[2, 3] and other adverse health outcomes[4–8].

41 However, epigenetic clocks suffer from several limitations that limit
42 the interpretability of their predictions and the underlying mechanisms.
43 Epigenetic clocks are generally trained by using penalized regression based
44 methods that attempt to minimize the difference between the predicted
45 and observed value of age. As a result, as the error between predicted
46 and observed age is decreased, the associations between age acceleration
47 and mortality disappears[9]. Second generation epigenetic clocks attempt
48 to resolve this issue by fitting a measure of human health, rather than
49 age, and as a result these clocks are generally more sensitive to individual
50 health status[10–12]. However, while the response variable is modified in
51 these clocks the method used to fit the clock is largely the same. Epigenetic
52 clocks are generally trained using regularized regression models,
53 where the likelihood is maximized by minimizing the difference between
54 the observed and predicted response variable subject to the elastic net
55 penalty, λ_1 and λ_2 . Methylation sites that increase model error and are
56 influenced by other relevant factors such as smoking or obesity, may be
57 discarded during model fitting, thus limiting the ability of this approach
58 to account for the effects of these extraneous factors on epigenetic aging.

59 As an alternative to penalized regression based methods we previously
60 developed an evolutionary based model for epigenetic dynamics, the Epi-
61 genetic Pacemaker (EPM)[13, 14]. The EPM attempts to minimize the
62 difference between observed and predicted methylation values amongst a
63 collection of sites through the implementation of a conditional expectation
64 maximization algorithm[15]. Under the EPM the observed methylation
65 status of a collection of sites is modeled linearly with respect to an input
66 factor of interest, such as age. A hidden epigenetic state, that is related
67 to the initial factor, but not necessarily linearly, is learned through the
68 course of model fitting. The EPM can capture the non-linear relationship
69 between methylation and age[16] and outputs an interpretable model for
70 each site. However, both the EPM and regression based methods suffer
71 from the same limitation, which is that they are limited to a single trait
72 predicted by, or used to model, observed methylation patterns. In reality,
73 the observed methylation landscape is likely impacted by a variety of
74 factors that act simultaneously to produce the observed methylome of an
75 individual.

76 To overcome this limitation, we have developed a multidimensional
77 extension of the EPM, the Multi-State Epigenetic Pacemaker (MSEPM).
78 We show that the (MSEPM) can accurately model site specific methyla-
79 tion variation driven by several factors, and given a trained model, ac-
80 curately predict the values of the factors associated with an individual's
81 observed methylation profile in both simulated methylation datasets and
82 a large aggregate blood tissue methylation dataset. Importantly, as fac-
83 tors that explain the observed methylation profile of an individual are

84 added to the model the ability to model the factors and methylation
 85 values improves. Additionally, we show that sites with similar associa-
 86 tions to modeled factors cluster together and are enriched for specific
 87 transcription factors. Therefore, unlike traditional epigenetic clocks, the
 88 MSEPM allows us to study mechanisms that may underlie age associated
 89 methylation changes. In our large dataset of blood samples, we find that
 90 sites that increase methylation with age are enriched for bivalent promoters,
 91 and are proximal to genes that are lowly expressed in blood. These
 92 results suggest that positively age associated sites may not have a sig-
 93 nificant functional impact on aging traits. The MSEPM is available as
 94 a Python package with scikit-learn style syntax under a MIT license at
 95 <https://github.com/NuttyLogic/MultistateEpigeneticPacemaker>.

96 2 Methods

97 2.1 Multi-State Epigenetic Pacemaker Model

98 The MSEPM model describes the observed methylation at site i and for
 99 individual j , $\hat{m}_{i,j}$, as a weighted linear combination of k individual epi-
 100 genetic factors $p_{j,k}$.
 101

$$\hat{m}_{i,j} = r_i^0 + \sum_{k=1}^n p_{j,k} r_{i,k}$$

102 Where k epigenetic factors are weighted by k site specific epigenetic rates
 103 of change, $r_{i,k}$, and offset by a sites specific intercept term, r_i^0 . Site pa-
 104 rameters, $r_{i,k}$ and r_i^0 , are characteristic of the site and shared amongst all
 105 individuals while epigenetic factors, $p_{j,k}$, are characteristic of an individ-
 106 ual and are the same across all sites for that individual. In practice, the
 107 observed methylation value is also dependent on a normally distributed
 108 error term $\epsilon_{i,j}$.
 109

$$\hat{m}_{i,j} = r_i^0 + \sum_{k=1}^n p_{j,k} r_{i,k} + \epsilon_{i,j}$$

110 Under this model epigenetic factors are related to observable individ-
 111 ual factors $p_{k,j}^0$, such as chronological age, sex and cell types, but may
 112 be transformed relative to observable factors. The epigenetic age factor,
 113 for example, often has a non-linear relationship with the observed age[16].
 114 The MSEPM learns the appropriate transformation during model fitting
 115 to describe the observed methylation status linearly in terms of the epi-
 116 genetic age factor, but not linearly with age.

117 Given an input matrix $\hat{M} = [m_{i,j}]$ of methylation values for i sites
 118 and matched observable epigenetic factors $\hat{P}^0 = [p_{j,k}^0]$ for j individuals
 119 the objective of the MSEPM is to find the optimal values of $r_{i,k}$ and $p_{j,k}$
 120 that minimize the residual sum of square (RSS) error,

$$\epsilon_{i,j}^2 = (m_{i,j} - r_i^0 - \sum_{k=1}^n p_{j,k} r_{i,k})^2$$

121 This is accomplished through the implementation of a conditional ex-
 122 pectation maximization algorithm. The maximum likelihood (ML) values

of $r_{i,k}$ and r_i^0 can be solved using ordinary least squares (OLS) regression. Provided the ML estimates for $r_{i,k}$, the site coefficients are fixed and epigenetic factors, $p_{j,k}$, are updated by minimizing the RSS across all i sites using gradient descent,

$$p_{j,k}^{n+1} = p_{j,k}^n - \lambda \nabla F(p_{j,k})$$

where λ is a specified learning rate. The optimization is accomplished by alternating between optimizing $r_{i,K}$ and $p_{j,k}$ until the reduction in sum of the site RSS is below a specified threshold or a set number of iterations is reached. Importantly, while the ML values of $p_{j,k}$ are by definition linear with the methylation status at any site, the original input factors for $p_{j,k}^0$ may not be.

Provided a trained MSEPM model and an unobserved methylation matrix, epigenetic factors are estimated by calculating each independent OLS for solution all i sites given the $r_{i,k}$ coefficients set for the respective input factor. These epigenetic factors can then be used to find the expected methylation value using the trained individual site models where

$$E[m_{i,j}] = r_{i,0} + P_j \dot{R}_i$$

2.2 MSEPM Simulation Framework

We implemented a simulation framework using the MSEPM formulation evaluate the performance of the MSEPM model under various conditions. To simulate the association between methylation status and an observable factor we modeled the epigenetic factor $p_{k,j}$ as function of time, or age, and magnitude, $p_{k,j}^0$ with a non-linear transformation γ_k , where $p_{k,j} = Age_j p_{k,j}^{0,\gamma_k}$. In practice the value of the $p_{k,j}$ is often unknown and the association between methylation status and $p_{k,j}$ is inferred through the observable factor $p_{k,j}^0$.

Methylation sites were simulated by first randomly setting the dynamic range of the methylation site, $-1 < \delta < 1$ a site intercept, r_i^0 , and the site error, $\sigma_i \sim \mathcal{U}(0.025, 0.05)$. The dynamic range of the methylation site is described by the initial methylation value, $m_0 \beta(.2, .2)$, and the target methylation value, m_t , where the dynamic range is $\delta_i = m_t - m_0$. The value of m_t is set conditionally to ensure dynamic range is always larger than some specified threshold, θ , where $\theta \leq |\delta| \geq .r_i^0 \beta(.2, .2)$.

Simulated methylation sites are then randomly associated with a combination of zero, one, or multiple epigenetic factors. Rates for sites associated with multiple factors were set by sampling from a uniform distribution. The weighted factor rates are normalized so the input combination of traits describes the dynamic range of the simulated site, δ . If a site is associated with no factors the observed methylation status of a site is described by a random normal with a characteristic offset, $\hat{m}_i = r_{0,i} + N(\mu, \sigma)$.

2.3 Blood MSEPM Model Training

MSEPM models were trained using a large aggregate dataset of blood derived methylation data from 17 publicly available datasets[7, 17–32]. Illumina methylation 450K Beadchip methylation array IDAT files were

149 processed using minfi[33] (v1.34.0). Sample IDAT files were processed in
150 batches according to GEO series and Beadchip identification. Methylation
151 values within each batch were normal-exponential normalized using
152 out-of-band probes[34]. Blood cell types counts were estimated using a
153 regression calibration approach[35] and sex predictions were made using
154 the median intensity measurements of the X and Y chromosomes as im-
155 plemented in minfi[33]. Samples were filtered for quality control using the
156 the relative intensity of the methylated and unmethylated probes. Sam-
157 ples were used for downstream analysis if the sample median methylation
158 probe intensity was greater than 10.5 and the difference between the ob-
159 served and expected median unmethylation probe intensity is less than
160 0.4, where the expected median unmethylated intensity is described by
161 $E[intensity_{unmethylated}] = 0.66intensity_{methylated} + 3.718$. This resulted
162 in a total of 5687 samples.

163 We trained MSEPM models using data assembled from four GEO se-
164 ries[20, 22, 29, 36] ($n = 1605$). The samples were randomly split into train-
165 ing ($n = 1203$) and validation ($n = 402$) sets stratified by age. Methy-
166 lation values for all samples were quantile normalized by probe type[37]
167 using the median site methylation values across all training samples for
168 each methylation site. Training set blood cell type abundance estimates
169 were used to train a principal component analysis (PCA) model which
170 was then used to calculate cell type PCA estimates for the validation and
171 testing sets. Methylation sites were selected for modeling with MSEPM
172 if the site methylation values were correlated with age ($n = 276$), sex
173 ($n = 49$), CT-PC1 ($n = 120$), CT-PC2 ($n = 116$) or a combination of
174 factors ($n = 238$) by absolute pearson correlation coefficient. Where a
175 absolute pearson correlation coefficient greater than 0.7, 0.995, 0.92 and
176 0.64 for age, sex, CT-PC1 and CT-PC2 respectively. Sites with a sum of
177 absolute pearson coefficients across the four factors greater than 1.8 were
178 also included ($n = 238$) for a total of 778 methylation sites. Min-max,
179 (0-1), scalers were fit using the training input features. Validation and
180 testing sample features were transformed with the trained scalers. Age
181 was min-max scaled on a range from 0-100 years. MSEPM models were
182 trained with a learning rate of 0.01 with an iteration limit of 200.

183 2.4 Blood MSEPM Model Cluster Transcription 184 Factor Overlap Analysis

185 We evaluated the relationship between modeled sites, input factors and
186 regulatory transcription factors using overlap enrichment analysis. We
187 built a custom transcription factor reference set using ENCODE V4 tran-
188 scription factor chromatin immunoprecipitation[38, 39] (release 1.4.0 -
189 2.1.2) irreproducible discovery rate narrow bed peaks, which contains
190 peaks with high rank consistency between replicates, that were not au-
191 dited for non-compliance or errors. GRCh38 region coordinates were lifted
192 to GRCh37 coordinates using liftOver[40]. The overlap reference contains
193 714 transcription factor targets from 1621 accession IDs.

194 We then performed hierarchical clustering of the four factor MSEPM
195 model sites based on the similarity of their regression coefficients. Indi-

196 individual methylation site coefficients were first normalized by the standard
197 deviation of methylation values of the site among the training samples,
198 $r_{i,k}/\sigma_i$. A distance matrix was then created by taking the Euclidean
199 distance between the normalized site model coefficients. Sites were then
200 clustered using Ward's method which seeks to minimize within cluster
201 variance by minimizing the increase in the error sum of squares (ESS)
202 through successive cluster fusions. Clusters label by tree cutting at a
203 height of 18. All clustering analysis was carried out using SciPy v1.6.3[41].
204

205 Transcription factor enrichment analysis was performed with LOLA[42]
206 which assesses the genomic region set overlap between a set of query re-
207 gions and a set of reference regions, within a specified shared background
208 set, using Fisher's exact test. Overlap analysis was performed for sites
209 within a cluster against the ENCODE V4 reference region (1BP minimum
210 overlap) using all sites assayed with Infinium HumanMethylation450K
BeadChip as background.

211 212 **2.5 Clustering sites with age-associated increases in methylation**

213 To better understand age associated methylation in whole blood, we ex-
214 amined each site within MSEPM four factor blood model cluster 7 indi-
215 vidualy, as this cluster contains sites that have methylation that increases
216 with age but is not strongly affected by other factors. Using the EWAS
217 Data Hub (Xiong, et al. 2016), we validated our results by obtaining ad-
218 dditional methylation by age data in whole blood for each site in the cluster
219 (McCartney, et al. 2019). We created a matrix with every sample and its
220 associated methylation and age from cluster 7, then used age associated
221 methylation levels to create a clustered heatmap using the Matlab func-
222 tion Clustergram. We then clustered the tree into four groups which were
223 analyzed separately.

224 We also identified the genes that were proximal to each site using
225 Cistrome-GO (Li et al. 2019). We then examined the expression of the
226 genes across tissues in the Genotype-Tissue Expression (GTEx) database
227 database. We used the GTEx Multi Gene Query to find which tissues
228 those genes belonged to.

229 We utilized the Toolkit for Cistrome Data Browser [43, 44] for the
230 analysis of significant factors in each cluster. This allowed us to input
231 .bed files of each sub-cluster and generate a GIGGLE score for specific
232 transcription factors, histone marks, and chromatin regions to assess sig-
233 nificance of these elements. A GIGGLE score tailored ranking of loci
234 based on overlap of genomic features provided by the user[45].

235 **2.6 H3K4me3 enrichment analysis**

236 Enrichment of analysis for H3K4me3 (figure 7A) was carried out by down-
237 loading rpm normalized bigwig files of H3K4me3 ChIP-seq data from
238 epigenomesportal[46] for CD38+ B Cells and CD56+ NTK Cells (for both
239 0-5 years old and 60-65 years old individuals). Heatmaps of H3K4me3
240 were generated using deepTools2[47] using the computeMatrix and plotHe-
241 atmap function to plot the bigwig signal over genomic regions of cluster

242 7 as the BED input. The IGV genome browser[48] was used to generate
243 an image of the KCTD1 and IRS2 promoter regions shown in figure 7B
244 using downloaded bigwig tracks.

245 2.7 Analysis Environment

246 Analysis was carried out in a Jupyter[49] analysis environment. Joblib[50],
247 SciPy[51], Matplotlib[52], Seaborn[53], Pandas[54] and TQDM[55] pack-
248 ages were utilized during analysis.

249 3 Results

250 3.1 Simulated Methylation Associated Traits

We simulated individuals whose methylation is determined by four factors and their associated epigenetic factors: a uniform factor approximating age with a non-linear association with methylation status

$$q \sim \mathcal{U}(0, 100), s_{Age} = q^{0.5}, \text{Figure 1A-B}$$

a binary trait resembling sex, linearly associated with methylation status

$$q \sim B(1, .5), s_{Sex} = q, \text{Figure 1C-D}$$

a continuous normal (CN) phenotype a linear association with methylation status

$$q \sim \mathcal{N}(1, 0.1), s_{CN} = q, \text{Figure 1E-F}$$

and a continuous exponentially (CE) distributed trait with a linear association with methylation status

$$q \sim \frac{1}{20}e^{-x/20}, s_{CE} = q, \text{Figure 1G-H}$$

251 We simulated 90 methylation sites (Figure 1I). We then evaluated
252 the MSEPM model as follows. We simulated 1000 samples with the four
253 epigenetic factors described above. We then simulated methylation values
254 using the simulated site rates. Simulated samples were then split for train-
255 ing ($n = 500$) and testing ($n = 500$). MSEPM models were then fitted
256 using the values of the input factors, $p_{k,j}^0$. We generated 1000 simulated
257 datasets and fit MSEPM models using four combinations of input factors
258 (Age, Age-Sex, Age-Sex-CN, Age-Sex-CN-CE). Within each simulation,
259 epigenetic state predictions and methylation site predictions were made
260 for all testing samples. All models captured the nonlinear association be-
261 tween simulated age and methylation (Supp. Figure 1). As the number of
262 factors in the model is increased the mean absolute error (MAE) between
263 the predicted epigenetic states and the simulated epigenetic factors de-
264 creases (Figure 2A). Importantly, to accurately assess simulated age it is
265 necessary to account for the influence of the other simulated factors (Sex,
266 CN, CE). The MAE between the predicted and simulated methylation
267 values decreases as simulated factors are added to the model, and accu-
268 rately assessing the methylation status of a simulated site requires that

269 the factor associated with the methylation status at the site is included
270 in the model (Figure 2A).

271 The MSEPM model generated using all four simulated factors can
272 capture the relative magnitude of the simulated site-specific rates (Figure
273 2C-F). However, the model has difficulty capturing the exact relationship
274 between the simulated factors (age, CN and CE) and the inferred factors
275 (Figure 2C, E-F). This is likely due to limitations of the model at cap-
276 turing nonlinear methylation association and a limited training range for
277 normally and exponentially distributed traits. Regardless, the four-factor
278 model can accurately predict the simulated methylation value (Figure 2
279 D) and site intercept (Supp. Figure 1A). We also assessed the model ro-
280 bustness to variation in the number of samples and sites used for model
281 training by randomly selecting a reduced subset of samples or sites for
282 model training. MSEPM models trained with age, sex, CN, and CE can
283 accurately assess all simulated phenotypes with few samples and sites
284 (Supp. Figure2 B-E).

285 3.2 Blood MSEPM Model

286 We next applied the MSEPM to real data. We utilized a large aggregated
287 dataset composed of Illumina 450k array data from 17 publicly available
288 datasets[7, 17–32] deposited in the Gene Expression Omnibus[56] (GEO)
289 generated from blood derived samples (whole blood, peripheral blood lym-
290 phocytes, and peripheral blood mononuclear cells). The aggregate data
291 spanned a wide age range (0.0 - 99.0 years, Figure 3A), contained more
292 predicted females ($n = 3392$) than males ($n = 2295$, Figure 3B) and rea-
293 sonable predicted cell type abundance estimates (Figure 3C). The first
294 principal component of a PCA mode trained cell type abundance es-
295 timates (CT-PC1) is largely driven by the relative abundance of gran-
296 ulocytes (Figure 3D), while the second PC (CT-PC2) captures relative
297 differences in the abundance of differentiated lymphocytes (Figure 3D).

298 We trained MSEPM models using methylation sites ($n = 778$) that
299 were correlated with the observable input factors. MSEPM models were
300 fit using four combinations of input factors (Age, Age Sex, Age Sex CT-
301 PC1, and Age Sex CT-PC1 CT-PC2). The association between the fit epi-
302 genetic factor predictions against the input modeled factors was assessed
303 by fitting a trendline between epigenetic state predictions and scaled con-
304 tinuous input factors using the state prediction made for the MSEPM
305 model trained with all four input factors. Performance of the MSEPM
306 model was then evaluated using the testing samples ($n = 4,082$). The per-
307 formance of the MSEPM largely closely resembles the simulation results.
308 All four MSEPM models capture the nonlinear relationship between age
309 and methylation status (Supp. Figure 6). The epigenetic state prediction
310 associated with age improves as the underlying methylation data are more
311 fully explained through the addition of epigenetic factors (Supp. Figure
312 6). The MSEPM model fit with Age, Sex, CT-PC1 and CT-PC2 can
313 accurately model the associated epigenetic state for each factor (Figure
314 4 A-D) and accurately predicts the methylation levels at individual sites
315 ($R^2 = 0.935$, $MAE = 0.035$, Figure 4 E). The trained MSEPM produces a
316 collection of methylation site models that can help explain the association

317 between modeled factors and methylation status.

318 **3.3 Analysis of chromatin regulators of site clus-
319 ters**

320 We evaluated the relationship between sites that are influenced by age,
321 sex, CT-PC1 or CT-PC2 and potential regulatory factors by performing
322 overlap enrichment analysis of these sites with transcription factor chro-
323 matin immunoprecipitation peaks present in the ENCODE V4[38, 39] re-
324 lease. We first identified sites with similar coefficients of epigenetic factors
325 through hierarchical clustering. The resulting tree was cut at a height of
326 18 to produce 10 distinct clusters with clear associations to the modeled
327 factors (Figure 5A).

328 The site clusters largely conform to underlying biological expectations.
329 Cluster one contains sites that are wholly associated with sex status and
330 localized to the X chromosome (Supp. Table 1) and is enriched for peaks
331 of transcription factors associated with sex specific regulation such as
332 MAZ[57]. Clusters nine and ten contain sites whose methylation sta-
333 tus is largely driven by CT-PC1, and are enriched for transcription fac-
334 tors associated with granulocyte development (CEPB, CEBPA, EP300,
335 ETV6)[58, 59]. Similarly, clusters two, five and eight are associated with
336 CT-PC2 and are enriched for transcription factor peaks associated with
337 immune development (ZBED1, ETV6, FOSL2, FOS, TBX21). Clusters
338 four and six are associated with loss of methylation with age. Cluster six
339 is highly enriched for CTCF binding sites; CTCF is known to increase
340 at sites where methylation is lost during aging[60]. Cluster four is en-
341 riched for STAT3 whose activation during exercise is age dependent[61,
342 62]. Cluster seven is associated with the accumulation of methylation
343 with age and is enriched for immunoprecipitation peaks for aging as-
344 sociated transcription factors SMAD4 and RE1-Silencing Transcription
345 Factor (REST). SMAD4 encodes a protein involved in the transforming
346 growth factor beta (TGF- β) signaling pathway. Age related dysregulation
347 of TGF- β has been linked to reduced skeletal muscle regeneration[63, 64]
348 and SMAD4 polymorphisms are associated with longevity[65]). REST
349 is a transcriptional repressor of neuron specific genes in non-neuronal
350 cells[66, 67]. REST expression is upregulated in aged prefrontal cortex
351 tissue and the absence of REST expression is associated with cognitive
352 impairment[68] and cellular senescence in neurons[69]).

353 **3.4 Analysis of sites with age-associated increases
354 in methylation**

355 Because of our interest in the mechanisms that underlie ages associated
356 increase in methylation, we focused on cluster seven, as these sites have
357 methylation increases that depend primarily on age rather than sex and
358 cell types. Cluster 7 consisted of 93 CpG sites. To obtain an independent
359 measure of how these sites change with age, we obtained age associated
360 methylation

361 data from the EWAS Data Hub[70], with a focus on whole blood

362 methylation. The dataset consisted of about 1600 individuals with ages
363 ranging from 0 to 113 years old[71]. We clustered the sites based on age
364 associated methylation levels, meaning the rate of methylation based on
365 age for each marker. Each site was organized into an ordered matrix with
366 methylation levels at each age, then grouped into four sub-clusters: A,
367 B, C, and D. As seen in Figure 6A, Cluster A had the highest average
368 methylation across ages, and each consecutive cluster had a decrease in
369 average methylation. We next examined chromatin accessibility, tran-
370 scription factors, histone marks, and genes associated with each cluster.
371 As shown in Supp. Figure 7, genes proximal to Cluster 7 sites were lowly
372 expressed in blood compared to other tissues. We analyzed chromatin ac-
373 cessibility, transcription factors, and histone marks associated with these
374 four groups. We computed levels of H3K27ac, H3K27me3, H3K4me3, and
375 H3K9me3 across the four subclusters. As seen in Figure 6C, H3K4me3
376 increased from clusters A through D. Figure 6E shows that H3K27ac in-
377 creased from clusters A through C, but then decreased in D. These results
378 suggest that subcluster D is enriched for bivalent domains, characterized
379 by H3K4me3 and H3K27me3.

380 Based on these results we hypothesize that the mechanisms that un-
381 derlies the gain of methylation with age at these bivalent promoters is the
382 age-associated loss of H3K4me3. It is well established that the presence
383 of trimethylation on H3K4 inhibits de novo methylation, and this effect
384 explains the hypomethylation that is typical of promoters, including biva-
385 lent promoters. We therefore hypothesize that the gain of methylation at
386 these sites may be caused by an age associated loss of H3K4me3. In or-
387 der to demonstrate that H3K4me3 decreases with age for genomic regions
388 where DNA methylation increases, we used published H3K4me3 ChIP-seq
389 data from epigenomesportal[46]. We selected two different blood cell types
390 CD38+ B Cells and CD56+ NTK Cells and plotted the H3K4me3 signal
391 of young (0 to 5 years old) versus old individuals (60 to 65 years old) over
392 genomic regions of cluster 7 (Figure 7A). Our analysis shows that younger
393 individuals have higher levels of H3K4me3 compared to older ones (Figure
394 7A) as also shown for two selected genomic loci of cluster 7 (the promoters
395 of KCTD1 and IRS2 genes) where we can observe a marked decrease in the
396 levels of H3K4me3 as age increases (Figure 7B). All together these data
397 suggest that genomic regions whose DNA methylation is increased with
398 age exhibit an age dependent loss of H3K4me3, thus showing an inverse
399 correlation between DNA methylation and H3K4me3 at these genomic
400 loci.

4 Discussion

401 Epigenetic clocks are widely used tools to study human aging and health.
402 Despite their widespread use, the biological interpretability of the mod-
403 els is limited. A methylome is influenced by many different biological
404 processes occurring simultaneously over time that may differ among indi-
405 viduals. Epigenetic clocks, while producing accurate predictions of age,
406 attempt to capture this complexity through a single dependent variable.
407 Additionally, the penalized regression based methods used to fit most epi-

409 genetic clocks select sites that minimize, or regress out, the influence of
410 other factors and omit groups of sites that are correlated. To overcome
411 these limitations, here we propose a multidimensional extension of the
412 EPM model, the MSEPM.

413 In contrast to previous methods, the MSEPM aims to simultaneously
414 model the effect of multiple factors on the methylome. The simulation
415 and blood MSEPM models show that concurrently modeling age, cell
416 type composition and sex can minimize model residuals when compared
417 with the MSEPM model fit with age only. The residual of the age only
418 model is often interpreted as a measure of age acceleration. When multiple
419 methylome associated traits are modeled simultaneously this residual can
420 be explained directly by other factors and the association between the
421 methylome and a trait of interest can be inferred.

422 Additionally, the individual methylation site linear models fit as part of
423 the MSEPM optimization can provide information about the relationship
424 between modeled factors and site specific biology. To this end, we find
425 that the blood MSEPM model conforms to expected biology. Sites with a
426 strong sex association localize to the X chromosome and sites associated
427 with cell types are enriched for transcription factors associated with the
428 development of immune cells.

429 CpG sites that are primarily affected only by age in the blood MSEPM
430 model are of particular interest. As others have previously described,
431 sites that progressively lose methylation over time are strongly enriched
432 for CTCF[72, 73]. As CTCF plays a key role in long range chromatin
433 interactions, this may suggest that there are age-associated changes in
434 three dimensional chromatin structure, and that the structure may be-
435 come more disordered with age. In fact, alterations in CTCF binding and
436 function with age have been implicated in the pathogenesis of various age-
437 related diseases, including cancer. For example, changes in the chromatin
438 structure and gene expression due to altered CTCF binding can contribute
439 to the genomic instability and altered cell proliferation characteristic of
440 cancerous cells (Hnisz et al., 2016; Phillips et al., 2009).

441 We identified a cluster of sites that showed increasing methylation
442 with age and that were not significantly affected by other factors. We
443 found that these sites are enriched for the transcription factor REST.
444 The RE1-Silencing Transcription Factor (REST), also known as Neuron-
445 Restrictive Silencer Factor (NRSF), is a key regulatory protein involved
446 in the development and differentiation of neurons. It plays a crucial role
447 in neurogenesis, neuronal differentiation, and in the maintenance of the
448 neuronal phenotype by regulating gene expression[74]. REST achieves
449 this by binding to the neuron-restrictive silencer element (NRSE) or RE1
450 sites in the DNA, leading to the repression of gene transcription in non-
451 neuronal cells or in neuronal progenitor cells, ensuring that neuronal genes
452 are expressed only in neurons[66, 75, 76]. The fact that this factor is
453 enriched at the positively age-associated sites suggests that these sites are
454 likely expressed in neuronal cells but not in blood. In fact this is what we
455 find when we examine the tissue specific expression of the genes proximal
456 o these sites.

457 We also examined the histone modifications associated with the posi-
458 tively age-associated sites and found that they were enriched for H3K4me3

459 and H3K27me3. These sites are characteristic of bivalent promoters. Bi-
460 valent promoters play a crucial role in the regulation of gene expression
461 during development and differentiation. Characterized by the simultaneous
462 presence of both activating (H3K4me3) and repressive (H3K27me3)
463 histone modifications, bivalent promoters mark genes that are poised for
464 transcription but are not actively transcribed. This dual modification
465 serves as a regulatory mechanism, ensuring that genes essential for differ-
466 entiation and development are ready to be activated at the appropriate
467 time. Bivalent domains are predominantly found in embryonic stem cells
468 and are crucial for maintaining the cells in a pluripotent state, allowing
469 for the rapid activation or repression of gene expression in response to de-
470 velopmental cues. The significance of bivalent promoters extends to their
471 role in cell fate decisions, where they contribute to the tight control of de-
472 velopmental pathways and the maintenance of stem cell identity[77, 78].
473 Our results suggest that the bivalent promoters we identified in blood are
474 inactive (as seen by the fact that the proximal genes are not expressed).
475 However, the fact that DNA methylation at these sites increases with age
476 suggests that they may be losing H3K4me3 with age. H3K4me3 is a crit-
477 ical regulator of DNA methylation as it inhibits the binding of DNMT3
478 to histones, as the DNMT3 ADD domain preferentially binds to the un-
479 methylated H3K4 residue[79]. This explains why promoters, which are
480 enriched for H3K4me3, are generally hypomethylated. Our results sug-
481 gests that there must therefore be an age associated loss of H3K4me3 at
482 these bivalent promoters. That is in fact what we saw when we examined
483 these marks in B cells and Nk cells of both young and old individuals.
484 These mechanisms further suggest that the age associated DNA methyla-
485 tion increases may not have a functional consequence in blood and that
486 their proximal genes remain repressed throughout life.

487 In conclusion, we introduced a multi-dimensional extension of the Epi-
488 genetic Pacemaker, the MSEPM. The MSEPM is capable of accurately
489 modeling multiple methylation associated factors simultaneously. This
490 paradigm can elucidate the site specific regulation underpinning methy-
491 lome dynamics. It allows us to characterize the mechanims underlying
492 age associated increases in methylation sites, suggeting that these were
493 caused by the loss of H3K4Me3 at bivalent promoters of genes that are
494 silenced in blood. The MSEPM is available under the MIT license at
495 <https://github.com/NuttyLogic/MultistateEpigeneticPacemaker>.

496 4.1 Supplementary Information

497 All analysis code, data processing code, and supplementary material asso-
498 ciated with this manuscript can be found at <https://github.com/NuttyLogic/MSEPMManuscript>.
499 The methylation simulation utility can be found at <https://github.com/NuttyLogic/MethSim>.
500 The data supporting these findings are openly available at GEO un-
501 der the series GSE87640, GSE87648, GSE51057, GSE51032, GSE87571,
502 GSE125105, GSE42861, GSE69138, GSE111629, GSE128235, GSE121633,
503 GSE73103, GSE61496, GSE59065, GSE97362, GSE156994, GSE128064
504 and GSE43976.

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510 **6 Ethical Statement/Conflict of Interest**

511 We have no conflicts of interest to disclose.

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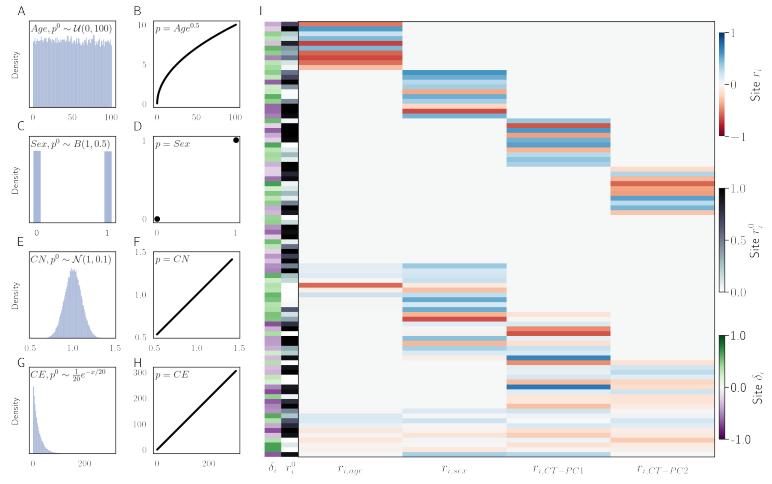


Figure 1: Simulated factors and the association with simulated methylation values. (A) Age with a non-linear association with methylation (B). Sex (C) with a binary association with methylation (D). Normal factor (E) with a linear relationship with methylation (F). Continuous exponential trait (G) with a linear relationship with methylation. (I) Simulated methylation sites. Each simulation site has a starting methylation value r_i^0 , rate of change associated with each simulated factor $r_{i,factor}$ and range of variation δ_i .

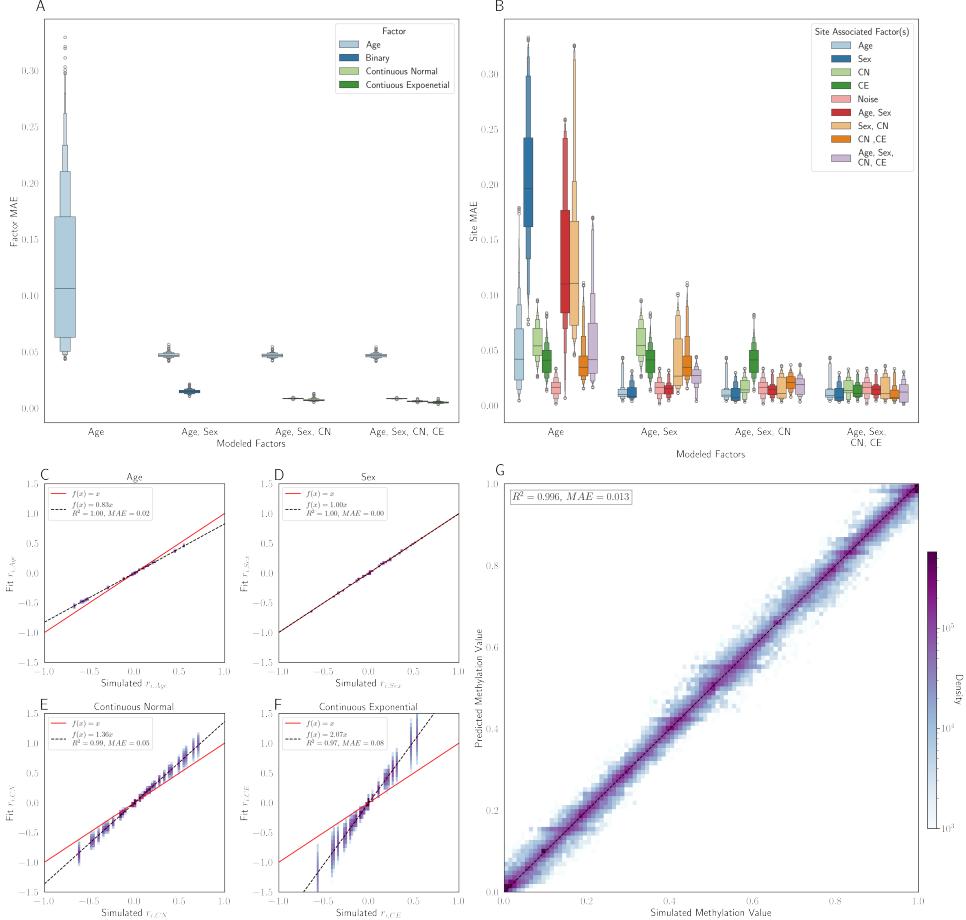


Figure 2: (A) The MAE of the factor predictions on the testing set as multiple factors are modeled simultaneously and (B) predicted methylation MAE as factors are included in the MSEPM model where the centerline is the 50th quantile and the box with greatest width contains 50% of the underlying data with each smaller box containing 50% of the remaining data with 6 levels of box width. (C) Model coefficients for Age, Sex, Continuous Normal and Continuous Exponential factors for models trained ($n = 500$) with all four simulated factors. (D). Simulated and predicted methylation values for all simulated testing sites across all training fold

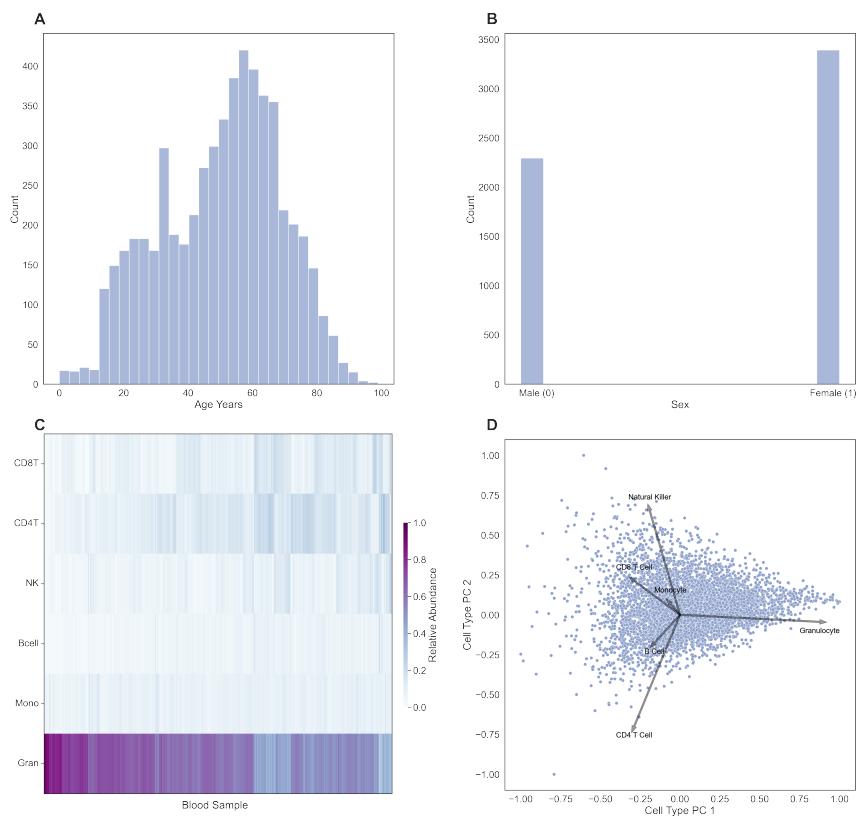


Figure 3: Distribution of age (A) and (B) sex in aggregate blood dataset. (C) Calculated cell type composition and (D) loading plot of principal components of cell type composition in aggregate blood data set.

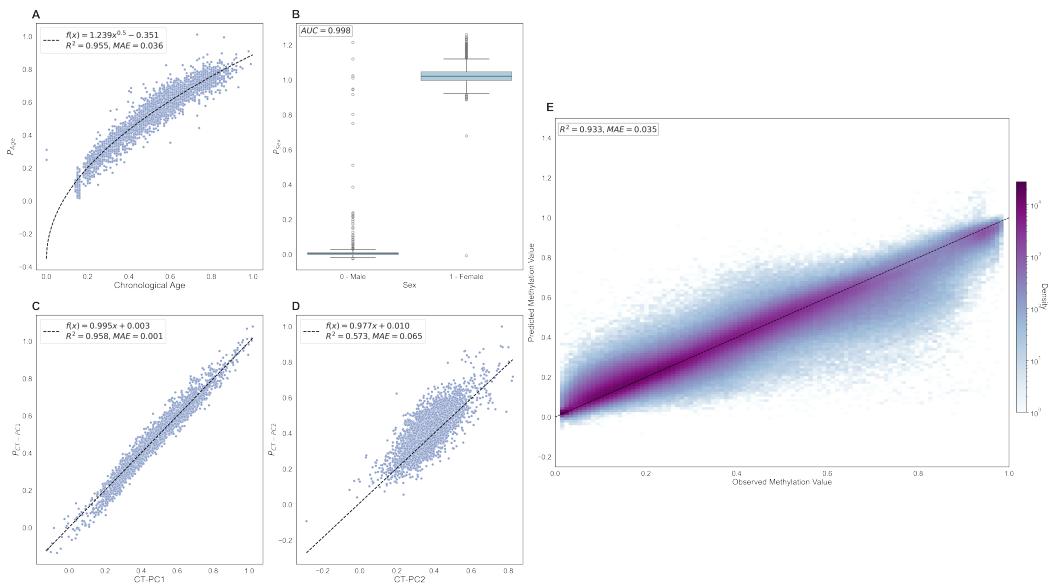


Figure 4: MSEPM model trained with age, sex, CT-PC1 and CT-PC2 predictions within testing set for epigenetic factors (A) age, (B) sex, (C) CT-PC1 and (D) CT-PC2. (E) Observed and predicted methylation values for training set has high concordance ($R^2 = 0.933$, $MAE = 0.035$)

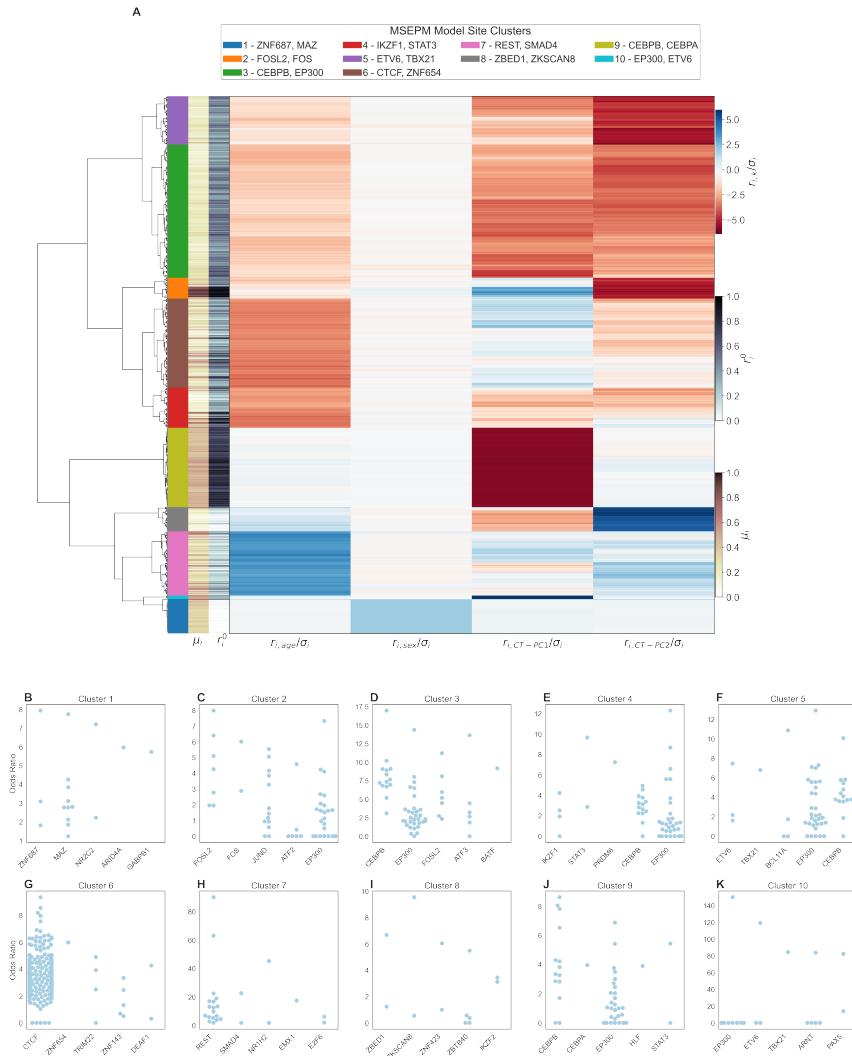


Figure5: (A) Site clustering by standardized model coefficients. Sites clusters show distinct relationships with modeled traits. (B-K) Top five enriched transcription factors for clusters 1 - 10.

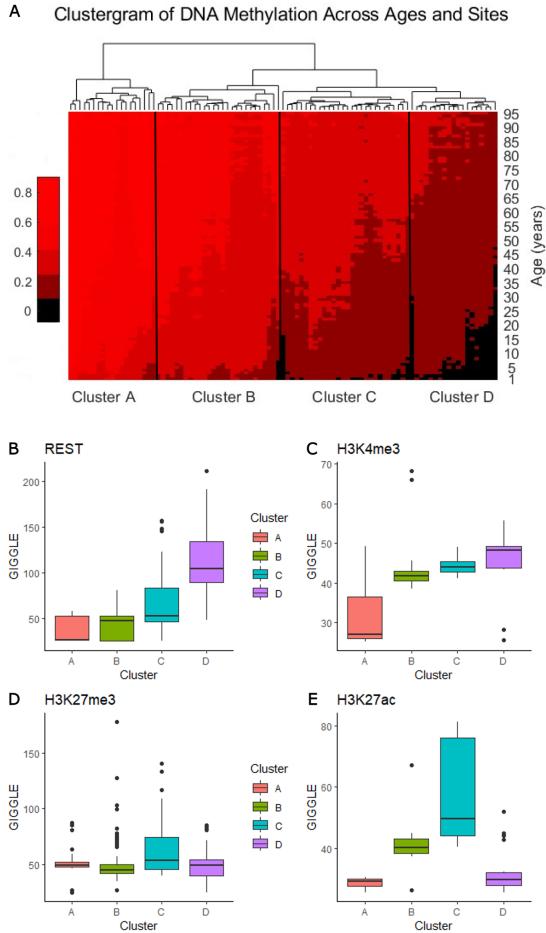


Figure6: (A) Heatmap of H3K4me3 ChIP-seq enrichment for two different blood cell types ($CD38^+$ B Cells and $CD56^+$ NTK Cells) in two cohorts of individual within 0 to 5 years old and 60 to 65 years old. The average level within 2kb up and downstream for centered genomic regions of cluster 7 is represented above the heatmap. (B) Genome browser view of H3K4me3 levels in each cohort at the promoter regions of *KCTD1* and *IRS2* genes.

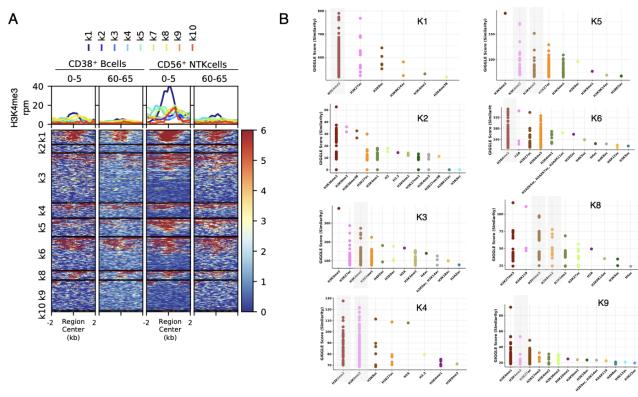


Figure 7: (A) Heatmap of H3K4me3 ChIP-seq enrichment for two different blood cell types (CD38⁺ B Cells and CD56⁺ NTK Cells) in two cohorts of individual within 0 to 5 years old and 60 to 65 years old. The average level within 2kb up and downstream for centered genomic regions of cluster 7 is represented above the heatmap. (B) Genome browser view of H3K4me3 levels in each cohort at the promoter regions of *KCTD1* and *IRS2* genes.