

# Sequence Analysis of Neighborhood Racial and Ethnic Changes: The Case of New York City 1980-2020

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This paper demonstrates the application of sequence analysis to develop a typology of racial and ethnic trajectories in New York City neighborhoods from 1980 to 2020 using a reproducible R workflow. Our workflow begins with using an unsupervised classification method, k-means, at each decennial cross-section to derive 6 classes describing the racial and ethnic makeup of neighborhoods during the study period. These classes include four that depict a majority of Black, White, Hispanic, and Asian residents, and two mixed-race classes, Black and Hispanic, and a White majority with a mixture of other races. We then develop a sequence of classes for each census tract over the 5 decennial time stamps. Finally, we derive a longitudinal typology describing the predominant pathways of change using sequence analysis. This resulted in 14 distinct pathways including transitions to Hispanic and Asian majorities emerging from historically White or Black neighborhoods. The findings underscore the gradual nature of neighborhood racial transformations. Our approach is reproducible for researchers wanting to explore and visualize multidimensional neighborhood dynamics.

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## Introduction

Tracking and understanding neighborhood changes has been a central topic of urban studies and a fundamental concern for planning practitioners (Galster 2001; Landis 2016; Chapple and Zuk 2016). Neighborhood change can be comprehended according to various dimensions, from housing stock or built environment changes to residents’ demographic and socioeconomic composition (E. C. Delmelle 2022). Thus, the study of neighborhood change involves analyzing multiple attribute dimensions through time for spatially situated units. Recent scholarship has progressed in the analytical strategies used to study neighborhood trajectories, introducing new methods for visualizing and mapping longitudinal pathways of change for multiple dimensions (E. C. Delmelle 2022).

In this article, we demonstrate one such technique, sequence analysis, in an illustrative, reproducible tutorial analyzing neighborhood change. We demonstrate the method using a case study of racial and ethnic changes in New York City census tracts from 1980-2020. While our focus is methodological, the empirical case study highlights the utility of sequence analysis in visualizing, detecting, and exploring longitudinal patterns of neighborhood changes.

Since the 1980s, The United States’ demographic profile has become increasingly diverse in the past several decades, driven by sustained immigration and by the growing share of births to non-White populations, influencing demographic shifts in the overall population structure (Frey 2022). Analyses following the release of the 2010 decennial census showed that increasing national diversity resulted in differing neighborhood trajectories, largely contingent on the broader metropolitan context (Terbeck 2023; Wright et al. 2014).

Much of the empirical scholarship on neighborhood racial and ethnic changes has developed indices to categorize the makeup or diversity of racial and ethnic groups and then explored changes in a neighborhood’s diversity categorization over time. For example, a neighborhood might transition from ‘low diverse’ to ‘moderately diverse’ from one decade to the next (Farrell and Lee 2011; Wright et al. 2014). Alternately, another set of techniques aims to describe the longitudinal sequences or trajectories that the racial and ethnic groups in a neighborhood have followed. Three methods have been adopted in the literature for this purpose: statistical curve fitting, time-series clustering, and sequence analysis. With curve-fitting models like growth mixture models or latent growth models, mathematical functions fit each racial and ethnic group under study that summarize the predominant trends (Zwiers, Ham, and Manley 2018; Hipp and Kim 2023a). Time series clustering is an unsupervised classification technique aimed at clustering continuous longitudinal data (Elizabeth C. Delmelle, Nilsson, and Duma 2025). Finally, in sequence analysis, neighborhoods are first grouped into similar categorical clusters at each time stamp. Then, each a sequence of neighborhood categories is constructed over time.

Finally, the sequences of these clusters are grouped using a sequence alignment technique (E. C. Delmelle 2016; González-Leonardo, Newsham, and Rowe 2023).

While all three approaches - curve fitting, time-series clustering, and sequence analysis aim to characterize change over time, they differ in what types of data and research questions they are best suited for. Curve fitting methods are well-suited for summarizing trends in continuous outcomes, especially when the trajectory is expected to follow a smooth or parametric form, which must be specified *a priori*. Time-series clustering also retains the continuous nature of longitudinal data, but must be performed on single variables at a time. Cross-sectional classes of trajectories can be constructed to form multivariate typologies (Elizabeth C. Delmelle, Nilsson, and Duma 2025), however, as the number of variables increases, this becomes an arduous workflow.

Sequence analysis is oriented towards categorical trajectories that can be constructed using multiple input variables, as demonstrated in this article. The method is particularly useful in visualizing and analyzing the timing, order, and transitions between qualitatively distinct neighborhood states rather than in the smoothness of changes.

In this article, we explore trajectories of neighborhood racial and ethnic changes in the largest and one of the most diverse cities in the United States, New York City, using longitudinal census data up to the latest 2020 decennial release. This notebook showcases a workflow that introduces sequence analysis to the study of multidimensional neighborhood changes. We begin by processing the raw longitudinal census data, then performing a k-means classification, and finally classify and map sequences clusters. Our case study illustrates the gradual progression that neighborhoods follow in when undergoing racial and ethnic transformations. We observe an overall decline in the share of neighborhoods categorized by a large White majority population, in exchange for increasing diversity, especially Hispanic and Asian populations.

## Computational environment

The main libraries used in this paper include `dplyr` for processing tabular census data, `sf` for mapping the resulting clusters, `cluster` for performing the `k-means` cluster analysis. Finally, to perform the sequence analysis, we use `TraMineR` (Gabadinho et al. 2011). This is a popular and continually updated R package for performing sequence analysis for a host of social science applications, including analyses of neighborhood change (E. C. Delmelle 2016, 2017; Patias, Rowe, and Cavazzi 2020).

## Data

We use decennial census tract data to examine neighborhood racial and ethnic changes. Census tracts serve as imperfect, yet well-used neighborhood proxies. Census tract boundaries change over time, further complicating the study of population dynamics within these boundaries. There are several sources of data that have been harmonized using interpolation techniques

to a consistent set of boundaries over time. We use the Longitudinal Tract Database (LTDB) which uses areal and population interpolation techniques alongside ancillary data on water cover to derive estimates (Logan, Xu, and Stults 2014). Analyses of the errors produced by three popular longitudinal data providers suggest that LTDB performs similarly to the dataset produced by the National Historic Geographic Information System (NHGIS) and both perform better than the Neighborhood Change Database which relies solely on areal interpolation without the inclusion of ancillary data (Logan, Xu, and Stults 2014). Therefore, for this type of analysis either the LTDB or NHGIS would be suitable dataset for this analysis.

We obtained the full count decennial data from LTDB from 1980-2020 from the [Diversity and Disparities project at Brown University](#). The census variables have been interpolated to 2010 tract boundaries. Because the coding of census race and ethnicity changes over time, we opted to begin in 1980 as 1970, the earliest dataset available, did not record a count of Latino or Hispanic residents. The raw data contains all census tracts throughout the United States. For visualization purposes, we also import a shapefile of 2010 census tract boundaries using the `tidycensus` package and setting the `geometry` to `true`.

```
setwd(here()) #current working directory

#csv tables for longitudinal data
census20<- read.csv("data/ltdb_std_2020_fullcount.csv")
census10<- read.csv("data/LTDB_Std_2010_fullcount.csv")
census00<- read.csv("data/LTDB_Std_2000_fullcount.csv")
census90<- read.csv("data/LTDB_Std_1990_fullcount.csv")
census80<- read.csv("data/LTDB_Std_1980_fullcount.csv")

#geometry data
#filter for NYC counties (5 boroughs)
nyc_counties <- c("Kings", "Queens", "New York", "Richmond", "Bronx")
tract <- get_decennial(geography = "tract",
                      variables = "P001001",
                      year = 2010,
                      state = "NY",
                      county = nyc_counties,
                      geometry = TRUE,
                      progress = FALSE)
```

We next calculate the share of White, Black, Hispanic, and Asian residents in each tract for each decade from the raw count using the total population as the denominator. We filter out tracts where the population is 0 and select only the relevant columns to create our data frame. We then join all columns from the five decennial data frames into one data frame called `census_all` and finally select only census tracts from the five counties that comprise New York City's five boroughs: Bronx County, Kings County (Brooklyn), New York County

(Manhattan), Queens County, Richmond County (Staten Island).

```
census80 <- census80 %>% filter (POP80 >0)
census80$perwhite80 <- census80$NHWHT80/census80$POP80
census80$perblack80 <- census80$NHBLK80/census80$POP80
census80$perhisp80 <- census80$HISP80/census80$POP80
census80$perasian80 <- census80$ASIAN80/census80$POP80
census80<- census80 %>% select(c("TRTID10","perwhite80", "perblack80", "perhisp80", "perasian80"))

census90 <- census90 %>% filter (POP90 >0)
census90$perwhite90 <- census90$NHWHT90/census90$POP90
census90$perblack90 <- census90$NHBLK90/census90$POP90
census90$perhisp90 <- census90$HISP90/census90$POP90
census90$perasian90 <- census90$ASIAN90/census90$POP90
census90<- census90 %>% select(c("TRTID10","state","county","perwhite90", "perblack90", "perhisp90", "perasian90"))

census00 <- census00 %>% filter (POP00 >0)
census00$perwhite00 <- census00$NHWHT00/census00$POP00
census00$perblack00 <- census00$NHBLK00/census00$POP00
census00$perhisp00 <- census00$HISP00/census00$POP00
census00$perasian00 <- census00$ASIAN00/census00$POP00
census00<- census00 %>% select(c("TRTID10","perwhite00", "perblack00", "perhisp00", "perasian00"))

census10 <- census10 %>% rename("TRTID10" = "tractid")
census10$perwhite10 <- census10$nhwht10/census10$pop10
census10$perblack10 <- census10$nhblk10/census10$pop10
census10$perhisp10 <- census10$hisp10/census10$pop10
census10$perasian10 <- census10$asian10/census10$pop10
census10<- census10 %>% select(c("TRTID10","perwhite10", "perblack10", "perhisp10", "perasian10"))

census20 <- census20 %>% rename("TRTID10" = "TRTID2010")
census20$perwhite20 <- census20$nhwt20/census20$pop20
census20$perblack20 <- census20$nhblk20/census20$pop20
census20$perhisp20 <- census20$hisp20/census20$pop20
census20$perasian20 <- census20$asian20/census20$pop20
census20<- census20 %>% select(c("TRTID10","perwhite20", "perblack20", "perhisp20", "perasian20"))

#join all data frames from each decade
census_all<- census90 %>% left_join(census00) %>% left_join(., census10) %>% left_join(., census20)

#Select NYC Counties. These include Bronx County, Kings County (Brooklyn), New York County (Manhattan), Queens County, Richmond County (Staten Island).
```

```

census_select <- census_all %>% filter((state == "NY" & county == "Bronx County")|
                                     (state == "NY" & county == "Kings County")|
                                     (state == "NY" & county == "New York County")|
                                     (state == "NY" & county == "Queens County")|
                                     (state == "NY" & county == "Richmond County"))

##remove NA values and state and county columns
census_nyc <- na.omit(census_select)%>% select(-state, -county)

#Select only the tractID column from the shapefile. Rename the field for ease of joining a
tract<- tract %>% select("GEOID")
tract<- rename(tract, TRTID10 = GEOID)
tract$TRTID10<- as.double(tract$TRTID10)

# Set tigris options to return the data in sf format (spatial data frame)
options(tigris_class = "sf")

# Download county boundaries for New York state
ny_counties <- counties(state = "NY", cb = TRUE,
                        progress = FALSE)

# Filter for only the New York City counties
nyc_counties <- ny_counties %>%
  filter(NAME %in% c("Bronx", "Kings", "New York", "Queens", "Richmond"))

# View the structure of the data
print(nyc_counties)

```

Simple feature collection with 5 features and 12 fields

Geometry type: MULTIPOLYGON

Dimension: XY

Bounding box: xmin: -74.25563 ymin: 40.4961 xmax: -73.70036 ymax: 40.91771

Geodetic CRS: NAD83

	STATEFP	COUNTYFP	COUNTYNS	AFFGEOID	GEOID	NAME	NAMELSAD
1	36	061	00974129	0500000US36061	36061	New York	New York County
2	36	047	00974122	0500000US36047	36047	Kings	Kings County
3	36	081	00974139	0500000US36081	36081	Queens	Queens County
4	36	085	00974141	0500000US36085	36085	Richmond	Richmond County
5	36	005	00974101	0500000US36005	36005	Bronx	Bronx County
	STUSPS	STATE_NAME	LSAD	ALAND	AWATER		geometry
1	NY	New York	06	58683880	29010416	MULTIPOLYGON	(((-74.00641 4...

2	NY	New York	06	179684484	71158757	MULTIPOLYGON	(((-74.04171 4...
3	NY	New York	06	281594048	188444349	MULTIPOLYGON	(((-73.96262 4...
4	NY	New York	06	148982680	117441532	MULTIPOLYGON	(((-74.16154 4...
5	NY	New York	06	109235674	39353304	MULTIPOLYGON	(((-73.77242 4...

## Basic conceptual intuition

### Categorizing Neighborhoods Using $k$ -means

Sequence analysis requires categorical input states. Given that neighborhood demographic and socioeconomic data is very often continuous, the first step is to transform the data into discrete categories for each year of the analysis. In this example, we opt to use a data-driven, unsupervised classification approach for this stage by applying  $k$ -means to cluster the racial and ethnic composition of each census tract in each decade into one of several mutually exclusive categories. This step serves as a preprocessing stage, not an analysis of changes itself.

As an alternative, for the case of racial and ethnic compositions, for example, pre-specified thresholds (e.g., >50% of a population group) could be used to define categories like “majority Black” or “majority Hispanic”. This approach works well in situations where clear theoretical cutoffs exist. However, other applications involving socio-economic indicators or multivariate neighborhood characteristics may not lend themselves to clear analyst-defined cutoffs, making a data-driven approach preferable. Since the purpose of this article is illustrative, we proceed with an overview of implementing  $k$ -means to construct the initial discrete classes of neighborhoods from the original racial and ethnic makeup data. However, if the analyst already has theoretically grounded thresholds, they can bypass this step and proceed directly to the sequence analysis.

In the context of neighborhood racial and ethnic classification, (Reibel and Regelson 2011) introduced the idea of using an unsupervised classification approach for studying neighborhood racial change as an alternative to the use of neighborhood diversity indices. The objective of the  $k$ -means algorithm is to group observations in such a way that maximizes the similarity of observations within groups or clusters while maximizing the dissimilarity between each cluster. In other words, the goal is to group neighborhoods so that those most similar to each other according to their racial and ethnic makeup are assigned to the same cluster and the clusters themselves are distinct from one another in terms of their makeup.

With the  $k$ -means algorithm, the number of clusters,  $k$  must be determined *a priori*. To make this determination, it is customary to evaluate multiple solutions using various fit statistics in conjunction with domain and geographic knowledge of the data (E. C. Delmelle 2015). It is also commonly recommended that input variables first be normalized to avoid placing unequal emphasis on variables that may be on different measurement scales. However, in our case study, all of the racial and ethnic variables represent percentages of the population and so this step is not performed in the case study.

Our ultimate goal is to understand the major pathways of neighborhood change and so each neighborhood will be classified five times for 1980, 1990, 2000, 2010, and 2020 to establish its longitudinal sequence. To ensure that the clusters are temporally stable, we will perform the clustering for all years at once. New neighborhood typologies may emerge over time with this approach. In that instance, only tracts from the later years would be assigned to the new cluster.

## Identifying pathways of change using sequence analysis

Like  $k$ -means, sequence analysis is an unsupervised classification technique but instead of grouping observations based on cross-sectional similarity, it clusters them based on the similarity of longitudinal categorical sequences. A central component of sequence analysis is defining how similar or dissimilar two sequences are. There are multiple methods to compute sequence dissimilarity. (Studer and Ritschard 2016) provides a comprehensive overview of various techniques for determining sequences dissimilarity for social science applications.

In this case study, our goal is to group neighborhoods that follow similar racial and ethnic change trajectories, specifically in which order of categories traverse through. This gives us an overview of the various pathways of change neighborhoods may take. For example sequences that progress from a majority White composition to Mixed Race and eventually to majority Hispanic may represent one frequent change pathway. Because our sequences are measured at fixed intervals (every decade from 1980 to 2020), and each neighborhood has the same number of observations, we are less concerned with irregular timing or duration, which are often central considerations in life-course studies.

To prioritize this kind of ordered similarity, we use OMstrans, a variation of the popular Optimal Matching (OM) algorithm (E. C. Delmelle 2017). OM treats sequences as strings and calculates the ‘edit distance’, or minimal cost to transform one sequence into another using insertions, deletions, and substitutions. In OMstrans, the algorithm operations not on the raw states, but on the transitions between states by merging each state in a sequence with its predecessor. This approach emphasizes how one state leads into another and helps preserve the sequencing of change.

For example, one neighborhood may have a sequence of *White, White, Mixed Race, Hispanic* while another neighborhood might follow the sequence *White, White, Mixed Race, Mixed Race*. Between these two strings, there is one entry that differs: the final state. To transform one to another, we could substitute *Hispanic* for *Mixed Race* in the second sequence, and the dissimilarity of the two sequences would be equal to the cost of that substitution.

In the OMstrans variant, distances between sequences of transitions are computed. This means that each state is merged with its previous state to create a subsequence. In the previous illustrative example, the first sequence becomes (*White-White, White-MixedRace, MixedRace-Hispanic*) and the OM cost evaluation is then applied to these subsequences.



The OMstrans approach allows us to incorporate empirical transition probabilities into the substitution cost matrix. In this way, frequent transitions (e.g., *White* to *Mixed*) are penalized less than rare ones. Insertions and deletions can be discouraged by assigning a higher cost than the empirical transitions so that disruptions to the temporal alignment of sequences is discouraged. The balance between preserving state similarity and order is further governed by the parameter  $w$ , the origin-transition parameter. When  $w = 1$ , OMstrans approximates the traditional OM algorithm. A lower value places greater emphasis on the ordering or sequencing of events than on the specific states themselves.

## Application

### Study Area

Our study area consists of census tracts within the five Boroughs of New York (see Figure below for an overview map).

```
# Filter for only the New York City counties
nyc_counties <- ny_counties %>%
  filter(NAME %in% c("Bronx", "Kings", "New York", "Queens", "Richmond"))

# Modify labels for specific counties
nyc_counties$label_main <- ifelse(nyc_counties$NAME == "New York", "New York",
                                ifelse(nyc_counties$NAME == "Kings", "Kings",
                                        ifelse(nyc_counties$NAME == "Richmond", "Richmond",
                                              nyc_counties$NAME)))

nyc_counties$label_paren <- ifelse(nyc_counties$NAME == "New York", "(Manhattan)",
                                  ifelse(nyc_counties$NAME == "Kings", "(Brooklyn)",
                                          ifelse(nyc_counties$NAME == "Richmond", "(Staten
                                                "")))

# Calculate centroids for each county to get coordinates for labels
centroids <- st_centroid(nyc_counties)
coords <- st_coordinates(centroids)

# Add the coordinates to the nyc_counties data frame
nyc_counties <- nyc_counties %>%
  mutate(X = coords[, 1],
         Y = coords[, 2])

# Adjust coordinates manually for specific counties
```

```

nyc_counties <- nyc_counties %>%
  mutate(
    X = ifelse(NAME == "New York", X - 0.11,
               ifelse(NAME == "Richmond", X + 0.012, X)), # Move "New York" left, Richmond
    Y = ifelse(NAME == "New York", Y + 0.005,
               ifelse(NAME == "Richmond", Y + 0.03, Y)) # Adjust Richmond label higher
  )

#you can mask water area if you would like.
#nyc_counties <- nyc_counties %>% erase_water(area_threshold = 0.9)

zoomed_map <- ggplot() +
  geom_sf(data = ny_counties, fill = "gray85", color = "white", size = 1) +
  geom_sf(data = nyc_counties, fill = "#85B0A9", color = "white", size = 3) +
  geom_segment(aes(x = -73.98, y = 40.775, xend = -74.03, yend = 40.775),
               color = "gray25", size = 0.5) +
  geom_text(data = nyc_counties, aes(x = X, y = Y, label = label_main),
            color = "black", size = 4, family = "Arial", fontface = "bold") +
  geom_text(data = nyc_counties, aes(x = X, y = Y - 0.02, label = label_paren),
            color = "gray25", size = 3.75, family = "Arial") +
  geom_text(aes(x = -73.6, y = 40.725, label = "Nassau"),
            color = "gray55", size = 4, family = "Arial", fontface = "bold") +
  geom_text(aes(x = -73.8, y = 40.98, label = "Westchester"),
            color = "gray55", size = 4, family = "Arial", fontface = "bold") +
  geom_text(aes(x = -73.6, y = 40.705, label = "(Long Island)"),
            color = "gray70", size = 3.5, family = "Arial", fontface = "bold") +
  annotation_scale(location = "bl", width_hint = 0.18,
                  text_cex = .9,
                  bar_cols = c("gray75", "white"),
                  style = "bar",
                  unit_label = "km") +
  coord_sf(xlim = c(-74.25, -73.5), ylim = c(40.4, 41.05), expand = FALSE) +
  theme_minimal() +
  theme(
    panel.grid.major = element_blank(),
    panel.grid.minor = element_blank(),
    axis.title = element_blank(),
    axis.text = element_blank(),
    legend.position = "none",
    plot.margin = margin(0, 0, 0, 0)
  )

```

```

# Create the large map for NY and surrounding counties with text annotation
inset_map <- ggplot() +
  geom_sf(data = ny_counties, fill = "gray90", color = NA, size = 1) + # All counties in g
  geom_sf(data = nyc_counties, fill = "#569289", color = "#569289", size = 5) + # NYC coun
  annotate("text", x = -76.2, y = 42.8, label = "New York State",
    size = 5.25, color = "gray49", angle = 0,
    alpha = 0.7, family = "Arial") + # Add text label
  theme_minimal() +
  theme(
    panel.grid.major = element_blank(), # Remove major grid lines
    panel.grid.minor = element_blank(), # Remove minor grid lines
    plot.title = element_text(hjust = 0), # Align title to the left
    plot.subtitle = element_text(hjust = 0), # Align subtitle to the left
    axis.title = element_blank(), # Remove axis titles
    axis.text = element_blank(), # Remove axis text (labels)
    plot.margin = margin(0, 0, 0, 0) # Tighten margins
  )

# Combine the maps, placing the inset map within the zoomed-in map
final_plot <- ggdraw() +
  draw_plot(zoomed_map) +
  draw_plot(inset_map, x = 0.07, y = 0.65, width = 0.3, height = 0.3) # Adjust position an

# Display the combined plot
print(final_plot)

```



Figure 1: Overview map of New York City five boroughs and surrounding counties

To begin our case study, we start by preparing the data for the  $k$ -means clustering. This involves pivoting the data frame so that each census tract is represented with five distinct rows, once for each decennial value. To do so, we pivot from a wide to a long format and select out just the four race and ethnicity values to be used in the clustering.

```

# Convert the data frame from wide to long format
census_long <- census_nyc %>%
  pivot_longer(cols = starts_with("per"),
               names_to = c(".value", "year"),
               names_pattern = "per(\\w+)(\\d{2})") %>%
  mutate(year = case_when(
    year == "80" ~ 1980,
    year == "90" ~ 1990,
    year == "00" ~ 2000,
    year == "10" ~ 2010,
    year == "20" ~ 2020,
    TRUE ~ as.integer(year)
  ))

data_for_clustering <- census_long %>%
  select(white, black, hisp, asian)

```

As explained above, the  $k$ -means clustering procedure requires that the number of clusters,  $k$  be specified *a priori*. There are fit statistics that attempt to determine the optimal number of clusters, considering the similarity of observations within each cluster and the distinctiveness of the clusters from each other. However, these mathematically-derived solutions are devoid of any contextual or theoretical understanding of the problem under study. Therefore, the selection of  $k$  often becomes more akin to art than a science (Von Luxburg, Williamson, and Guyon 2012), considering the objective of the study. We begin with two common data-driven approaches that explore multiple clustering solutions for different  $k$  values and then examines the *within sum of squares* (WSS) and the *average silhouette score* for each solution. The WSS assesses how compact a clustering solution is, or how homogeneous the observations assigned to each cluster are, and the average silhouette score measures how well separated each cluster is from each other. Our objective is to derive a typology of neighborhoods according to their racial and ethnic makeup, for four groups: percent White, Black, Hispanic, and Asian. The Figure below shows the results of the clustering analysis; the Elbow method plot suggests the optimal number of clusters, while the Silhouette method plot helps validate the cluster separation.

```

# Now do the k-means clustering on all

data_for_clustering <- census_long %>%
  select(white, black, hisp, asian)

# Function to calculate total within-cluster sum of squares for different k
wss <- function(k) {

```

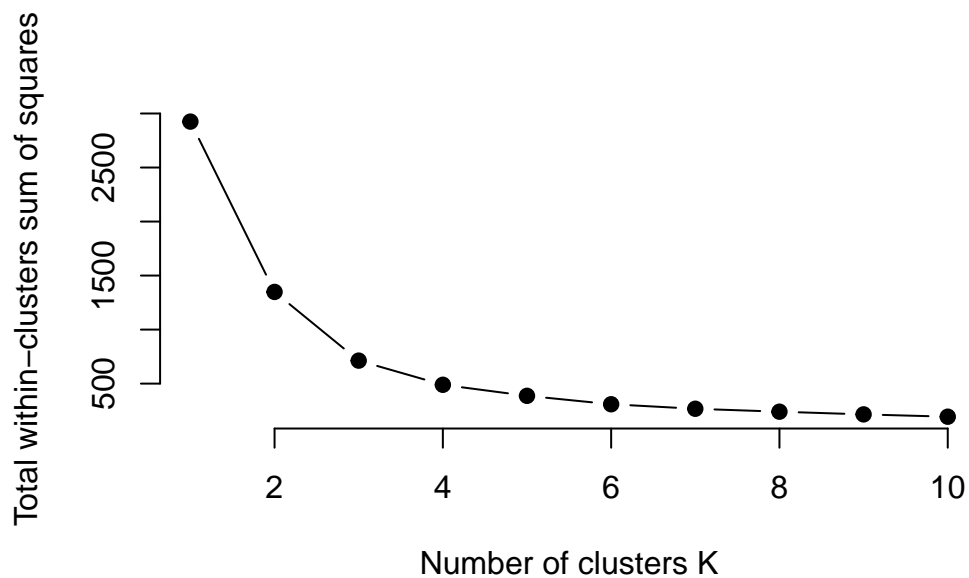
```

    kmeans(data_for_clustering, k, nstart = 10)$tot.withinss
  }

# Compute and plot wss for k = 1 to k = 10
k.values <- 1:10
wss_values <- map_dbl(k.values, wss)

# Elbow method plot
plot(k.values, wss_values, type = "b", pch = 19, frame = FALSE,
     xlab = "Number of clusters K",
     ylab = "Total within-clusters sum of squares")

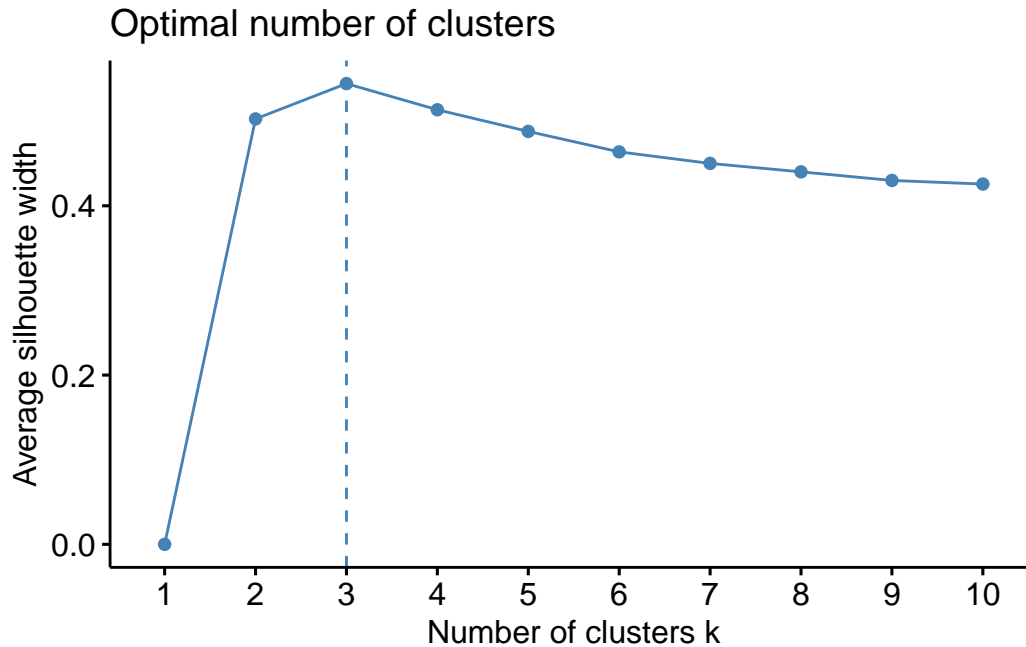
```



```

# Silhouette method for determining the optimal number of clusters
fviz_nbclust(data_for_clustering, kmeans, method = "silhouette")

```



### Exploring *k*-means Cluster Solutions

According to these plots, the mathematically optimal number of neighborhood clusters for racial makeup is three. We can further explore the makeup of neighborhoods within these three clusters a few ways to determine if, in fact, three clusters provides a meaningful segmentation of four distinct racial and ethnic groups. In the plots below, we can visualize the average silhouette value for each cluster. The *Silhouette* values range from -1 to 1; values close to 1 suggest that the observations are well clustered while negative values suggest that an observation might be assigned to the wrong cluster. From the plot, Clusters 2 and 3 appears to be the most cohesive clusters, with average silhouette widths of 0.64, while cluster 1 has some potentially poorly classified neighborhoods. Descriptions of the racial and ethnic makeup of the clusters are obtained from the associated stacked bar charts. We can see that Cluster 1 is characterized as being nearly 50 percent Hispanic, with near equal shares of Whites, Blacks, and Asians. Cluster 2 is majority Black with approximately 15 percent Hispanics and few Whites and Asians. Finally, Cluster 3 is majority White. Therefore, this segmentation provides us with clusters indicating the dominant racial groups, but may miss some nuances of other racial and ethnic neighborhood compositions. We can therefore explore how increasing *k* may portray a richer portrait of neighborhood demographic profiles. The Figure below illustrates the Silhouette Analysis to assess cluster separation, and the demographic makeup of the three clusters (bottom Figure).

```
# Assume the optimal number of clusters (k) is 3 from the previous steps
set.seed(123)
kmeans_result <- kmeans(data_for_clustering, centers = 3, nstart = 25)

# Add the cluster assignments to the original data
census_long$cluster <- kmeans_result$cluster

# Silhouette Analysis
sil <- silhouette(kmeans_result$cluster, dist(data_for_clustering))
fviz_silhouette(sil)
```

	cluster	size	ave.sil.width
1	1	3284	0.33
2	2	2478	0.64
3	3	4848	0.64

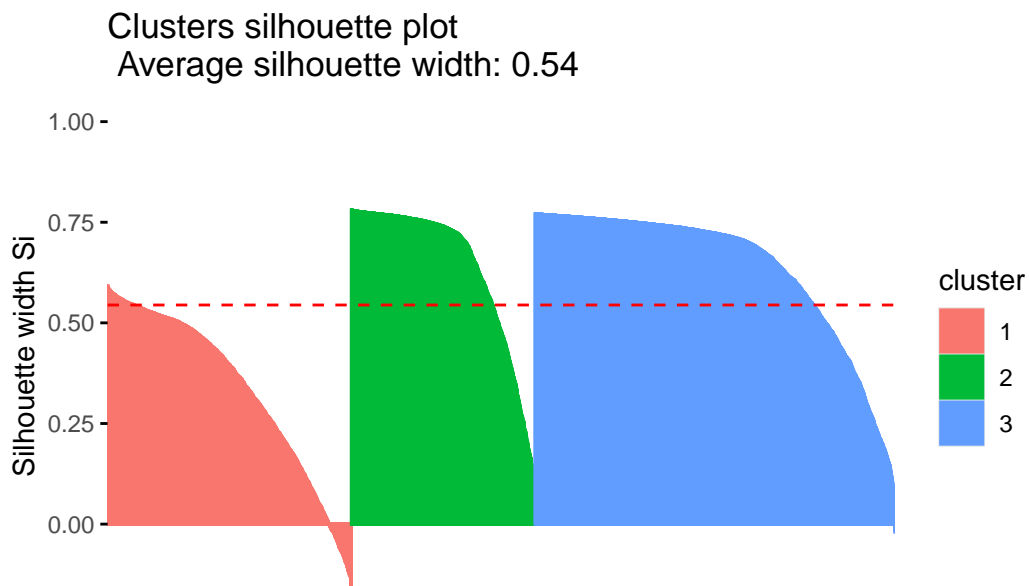


Figure 2: Cluster Analysis Results: Silhouette Analysis and Cluster Demographic Makeup

```
# Extract silhouette information to a data frame (df)
sil_df <- as.data.frame(sil[, 1:3])
colnames(sil_df) <- c("Cluster", "Silhouette Width", "Neighboring Cluster")

# Cluster profiles
```



```

cluster_profiles <- census_long %>%
  group_by(cluster) %>%
  summarise(across(c(white, black, hisp, asian), ~ round(mean(.), 2)))

# Print the table as a formatted table
kable(cluster_profiles, caption = "Cluster Profiles: Average Demographics",
      col.names = c("Cluster", "White", "Black", "Hispanic", "Asian"),
      format = "markdown")

```

Table 1: Cluster Profiles: Average Demographics

Cluster	White	Black	Hispanic	Asian
1	0.15	0.18	0.50	0.15
2	0.07	0.75	0.14	0.02
3	0.73	0.04	0.12	0.10

## Cluster Analysis Results: Silhouette Analysis and Cluster Demographic Makeup

```

# Reshape the data from wide to long format
cluster_profiles_long <- cluster_profiles %>%
  pivot_longer(cols = c("white", "black", "hisp", "asian"),
               names_to = "Demographic", values_to = "Proportion")

# Create the stacked bar chart
ggplot(cluster_profiles_long, aes(x = factor(cluster), y = Proportion, fill = Demographic)) +
  geom_bar(stat = "identity") +
  labs(title = "Cluster Demographic Makeup - 3 clusters", x = "Cluster", y = "Proportion") +
  scale_fill_manual(
    values = c(
      "white" = "#F0E442", # yellow
      "black" = "#0072B2", # blue
      "hisp" = "#D55E00", # orange/red
      "asian" = "#CC79A7" # magenta
    ),
    labels = c(
      "white" = "White",
      "black" = "Black",
      "hisp" = "Hispanic",
      "asian" = "Asian"
    )
  )

```

```

),
name = "Demographic Group"
) + # Adjust color palette if desired
theme_minimal()

```

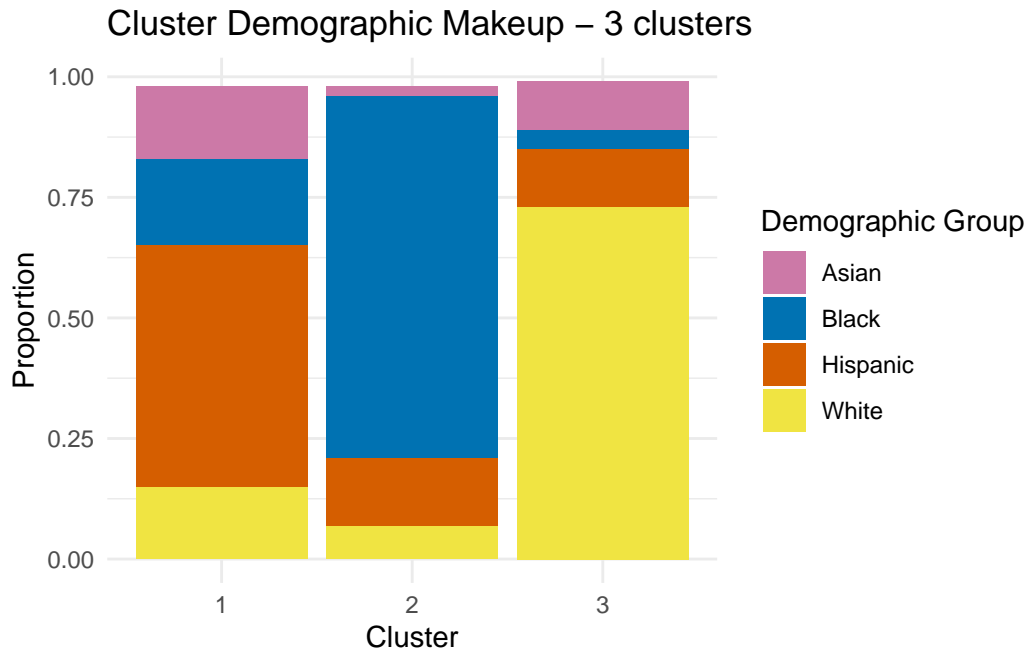


Figure 3: Cluster Analysis Results: Silhouette Analysis and Cluster Demographic Makeup

Next, we compare 4, 5, and 6 cluster solutions. We can see that the average silhouette of the solutions declines as the number of clusters increases. The demographic profiles show several new neighborhood typologies emerge with more clusters added. With a four cluster solution, we observe neighborhood typologies for each of the three dominant racial and ethnic groups: White, Hispanic, and Black along with one mixed neighborhood type, shown in cluster 4. As expected, that cluster displays the lowest silhouette value, with some potentially misclassified neighborhoods. The 5 cluster solution adds a cluster showing a majority Asian population, alongside two majority White populations - one showing more diversity than the other), and a majority Black, and Hispanic group. Finally, a 6 cluster solution shows more racially mixed groups, but at the expense of less well-defined or separated clusters. In the code below, each variable name ends with a number (4, 5 or 6), indicating which number of clusters (k) it represents. The results displays the silhouette analysis results for clustering into (a) four clusters, (b) five clusters, and (c) six clusters, illustrating the cohesion and separation of clusters at different sizes.

```

# Perform k-means clustering for 4, 5, and 6 clusters
set.seed(123)
kmeans_4 <- kmeans(data_for_clustering, centers = 4, nstart = 25)
kmeans_5 <- kmeans(data_for_clustering, centers = 5, nstart = 25)
kmeans_6 <- kmeans(data_for_clustering, centers = 6, nstart = 25)

# Add cluster assignment to original data
census_long$cluster_4 <- kmeans_4$cluster
census_long$cluster_5 <- kmeans_5$cluster
census_long$cluster_6 <- kmeans_6$cluster

# Silhouette analysis for 4, 5, and 6 clusters
sil_4 <- silhouette(kmeans_4$cluster, dist(data_for_clustering))
sil_5 <- silhouette(kmeans_5$cluster, dist(data_for_clustering))
sil_6 <- silhouette(kmeans_6$cluster, dist(data_for_clustering))

# Plot silhouette for 4 clusters
plot_4 <- fviz_silhouette(sil_4) + ggtitle("Silhouette Plot - Four Clusters")

```

	cluster	size	ave.sil.width
1	1	2091	0.49
2	2	2431	0.64
3	3	2265	0.20
4	4	3823	0.64

```

# Plot silhouette for 5 clusters
plot_5 <- fviz_silhouette(sil_5) + ggtitle("Silhouette Plot - Five Clusters")

```

	cluster	size	ave.sil.width
1	1	2130	0.48
2	2	3002	0.64
3	3	870	0.33
4	4	2417	0.64
5	5	2191	0.24

```

# Plot silhouette for 6 clusters
plot_6 <- fviz_silhouette(sil_6) + ggtitle("Silhouette Plot - Six Clusters")

```

	cluster	size	ave.sil.width
--	---------	------	---------------

1	1	1667	0.68
2	2	2152	0.27
3	3	843	0.34
4	4	2903	0.63
5	5	1246	0.26
6	6	1799	0.46

```
# Combine the three plots into a faceted view
grid.arrange(plot_4, plot_5, plot_6, ncol = 1)
```

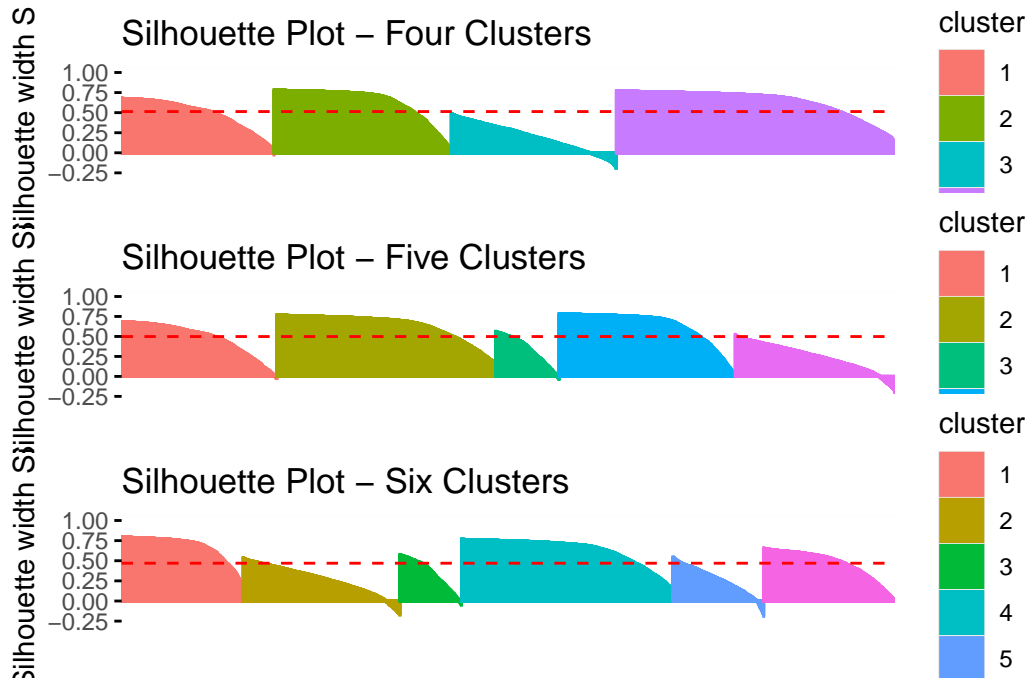


Figure 4: Silhouette Analysis for Different Cluster Sizes: (top) Four Clusters, (middle) Five Clusters, and (bottom) Six Clusters.

The figure illustrates the demographic composition of clusters for different clustering solutions: (a) four clusters, (b) five clusters, and (c) six clusters, highlighting how demographic groups are distributed across various cluster labels.

```
# We need to hard code the labels to be able to compare the demographic profile of each so
label_clusters <- function(cluster_profiles) {
  cluster_profiles %>%
    mutate(
      label = case_when(
```

```

    white > 0.75 ~ "3 White",
    hisp > 0.45 ~ "2 Hispanic",
    black > 0.75 ~ "1 Black",
    asian > 0.45 ~ "5 Asian",
    white < 0.56 & hisp > 0.20 & black < 0.20 ~ "4 Mixed",
    black > 0.49 & hisp > 0.25 & white < 0.15 ~ "6 Black & Hispanic",
    TRUE ~ "Other" # Default label if none of the conditions are met
  )
)
}

# Create cluster profiles and label them according to your custom rules
cluster_profiles_4 <- census_long %>%
  group_by(cluster_4) %>%
  summarise(across(c(white, black, hisp, asian), ~ round(mean(.), 2))) %>%
  mutate(`Clustering_Solution` = "4 Clusters", Cluster = cluster_4) %>%
  label_clusters()

cluster_profiles_5 <- census_long %>%
  group_by(cluster_5) %>%
  summarise(across(c(white, black, hisp, asian), ~ round(mean(.), 2))) %>%
  mutate(`Clustering_Solution` = "5 Clusters", Cluster = cluster_5) %>%
  label_clusters()

cluster_profiles_6 <- census_long %>%
  group_by(cluster_6) %>%
  summarise(across(c(white, black, hisp, asian), ~ round(mean(.), 2))) %>%
  mutate(`Clustering_Solution` = "6 Clusters", Cluster = cluster_6) %>%
  label_clusters()

# Combine all cluster profiles into one table
cluster_profiles_combined <- bind_rows(cluster_profiles_4, cluster_profiles_5, cluster_profiles_6)

# Map the labels back to the original tracts by joining based on cluster assignments
census_long <- census_long %>%
  left_join(cluster_profiles_4 %>% select(Cluster, label) %>% rename(label_4 = label), by = "Cluster")
  left_join(cluster_profiles_5 %>% select(Cluster, label) %>% rename(label_5 = label), by = "Cluster")
  left_join(cluster_profiles_6 %>% select(Cluster, label) %>% rename(label_6 = label), by = "Cluster")

# Reshape data for plotting
cluster_profiles_long <- cluster_profiles_combined %>%

```

```

pivot_longer(cols = c("white", "black", "hisp", "asian"),
             names_to = "Demographic", values_to = "Proportion")

# Plot stacked bar charts of demographic makeup for each labeled cluster
ggplot(cluster_profiles_long, aes(x = label, y = Proportion, fill = Demographic)) +
  geom_bar(stat = "identity", position = "stack") +
  facet_grid(Clustering_Solution ~ ., scales = "free_x") +
  scale_y_continuous(labels = scales::percent_format(accuracy = 1)) +
  scale_fill_manual(
    values = c(
      "white" = "#F0E442",      # yellow
      "black" = "#0072B2",     # blue
      "hisp"  = "#D55E00",     # red/orange
      "asian" = "#CC79A7"      # magenta
    ),
    labels = c(
      "white" = "White",
      "black" = "Black",
      "hisp"  = "Hispanic",
      "asian" = "Asian"
    ),
    name = "Demographic Group"
  ) +
  labs(
    title = "Demographic Makeup of Labeled Clusters (4, 5, and 6 Clusters)",
    x = "Cluster Label",
    y = "Proportion of Demographic Group"
  ) +
  theme_minimal() +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1),
    plot.title = element_text(hjust = 0.5, size = 13, face = "bold"),
    strip.text.y = element_text(angle = 0)
  )

```

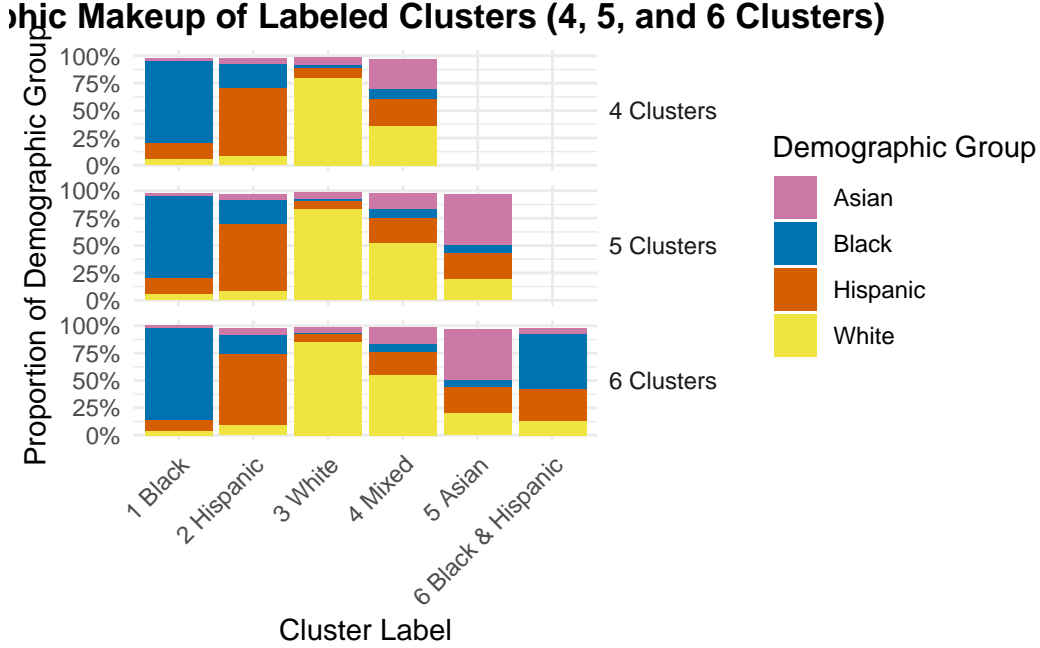


Figure 5: Geographic variation of Labeled Clusters for Different Clustering Solutions.

We can explore how this plays out for a specific observation. For example, take the first census tract in the data frame for the year 2020. This tract's racial composition was 58% Black and 30% Hispanic with small shares of Whites and Asians. With the four cluster solution, this tract was classified into class 1, **Majority Black**. For the five cluster solution, it was also classified as **Majority Black**, and for the six cluster solution, **Black and Hispanic**. In 1990, that same tract was 34% black and 61% Hispanic, resulting in the tract being classified as **Majority Hispanic** by all three clustering solutions. When looking at change over time, the neighborhood will either be registered as transitioning from **Majority Hispanic** to either **Majority Black** or **Black and Hispanic**, depending on the final cluster solution. In this instance, the 6 cluster solution provides a more accurate portrayal of the dynamics - while the neighborhood did technically become majority Black, there is still a significant Hispanic presence, a detail that would have been omitted by limiting the number of groups.

Finally, we can examine the spatial distribution of these clustering solutions to help aid in the final determination for the sequence analysis. Since we did the cluster analysis on all decades, for this purpose, we will contrast the 4, 5, and 6 cluster solutions just for 2020. All three maps depict a similar spatial pattern, but with a more fragmented pattern in the case of the 6 cluster solution. For example, the first two maps show contiguous tracts of the predominantly Black cluster, but the third map shows the emergence of the **Black and Hispanic** group largely forming on the outskirts of this spatial cluster. Another apparent distinction is the large spatial cluster of the **Asian** cluster in Queens, which had been labeled as **Mixed** in the 4 cluster solution.

To better understand details on racial neighborhood transitions, we will go with the larger number of clusters, 6, despite the mathematical preference for a 3 cluster solution. Our result illustrates the demographic distribution of labeled clusters for different clustering solutions: four clusters, five clusters, and six clusters.

```
# Filter data for the year 2020 and merge labels with tract data for mapping
tract_clusters_2020 <- tract %>% erase_water(area_threshold = 0.9) %>%
  left_join(census_long %>%
    filter(year == 2020) %>% # Filter for the year 2020
    select(TRTID10, cluster_4, cluster_5, cluster_6, label_4, label_5, label_6),
  pivot_longer(cols = c("cluster_4", "cluster_5", "cluster_6"),
    names_to = "ClusterSolution", values_to = "Cluster") %>%
  pivot_longer(cols = c("label_4", "label_5", "label_6"),
    names_to = "LabelSolution", values_to = "Label") %>%
  filter(str_replace(ClusterSolution, "cluster_", "") == str_replace(LabelSolution, "label_"))
  mutate(Label = factor(Label)) %>%
  mutate(ClusterSolution = recode(ClusterSolution,
    "cluster_4" = "4 Clusters",
    "cluster_5" = "5 Clusters",
    "cluster_6" = "6 Clusters")) %>%
  mutate(ClusterSolution = factor(ClusterSolution, levels = c("4 Clusters", "5 Clusters",

base_plot <- ggplot(tract_clusters_2020) +
  geom_sf(aes(fill = Label), color = NA) +
  geom_sf(data = nyc_counties, fill = NA, color = "black", size = 0.5) +
  facet_wrap(~ ClusterSolution, nrow = 1, strip.position = "bottom") +
  scale_fill_manual(
    values = c("3 White" = "#F0E442", "2 Hispanic" = "#D55E00",
      "1 Black" = "#0072B2", "5 Asian" = "#CC79A7",
      "4 Mixed" = "#009E73", "6 Black and Hispanic" = "#56B4E9"),
    labels = c("Black", "Hispanic", "White", "Asian", "Mixed", "Black & Hispanic")
  ) +
  labs(
    title = "Racial Cluster Maps by Number of Groups",
    x = "", y = "", fill = NULL
  ) +
  theme_void() +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold", size = 14),
    strip.background = element_blank(),
```



```

strip.placement = "outside",
strip.text = element_text(size = 12, face = "italic", color = "gray20"),
legend.position = "bottom",
legend.title = element_blank(),
legend.text = element_text(size = 8),
legend.key.width = unit(1.2, "cm"),
legend.key.height = unit(0.4, "cm")
) +
guides(fill = guide_legend(nrow = 1, byrow = TRUE, label.position = "bottom"))

grid.arrange(base_plot)

```

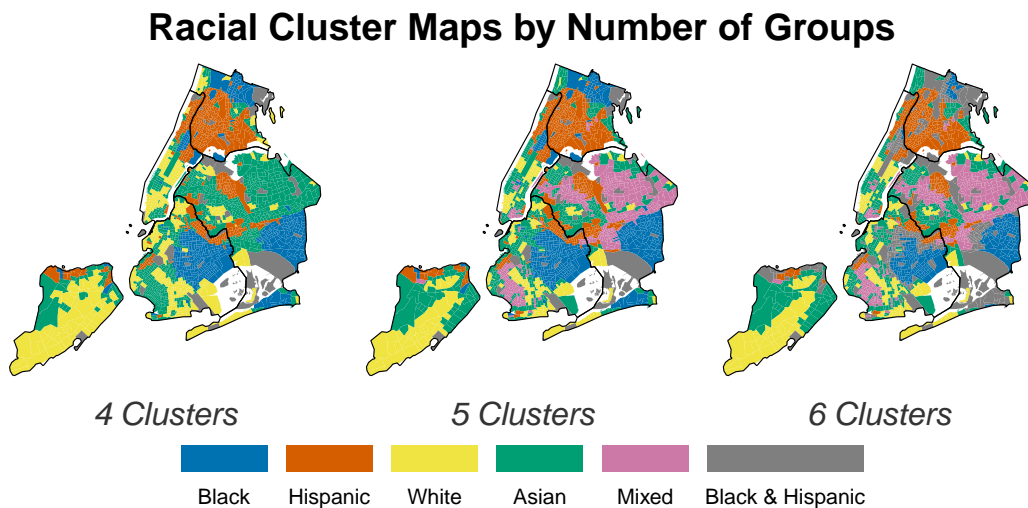


Figure 6: Demographic Distribution of Labeled Clusters for Different Clustering Solutions: Four Clusters (top), Five Clusters (middle), and Six Clusters (bottom).

We can begin with a simple exploration of the spatial changes over time in the maps showing the six clusters from 1980-2020 in a series of small multiples. From these maps, we can pick out some general spatial patterns over time. For example, we can see the expanse of neighborhoods classified as majority White from 1980 significantly diminishes by 2020. The share of Hispanics is shown to increase over time in the northern sections of the City. Towards the East, we see neighborhoods generally transition from predominantly White in 1980 to White and Mixed Race and eventually to Asian by 2020. There are also some evident stable clusters. For instance, the two clusters of predominantly black neighborhoods in the South and Southeast appear quite stable over time. However, the cluster of majority Black neighborhoods in towards the north of Manhattan is diminished, replaced by a Black and Hispanic classification.

```

decades <- c(1980, 1990, 2000, 2010, 2020)

# Filter and prepare data for mapping
tract_clusters_decades <- tract %>%
  left_join(census_long %>%
    select(TRTID10, year, label_6), by = "TRTID10") %>%
  filter(!is.na(label_6))

# Set factor levels for year to ensure proper ordering
tract_clusters_decades <- tract_clusters_decades %>%
  mutate(year = factor(year, levels = decades))

ggplot(tract_clusters_decades) +
  geom_sf(aes(fill = label_6), color = NA) +
  geom_sf(data = nyc_counties, fill = NA, color = "black", size = 0.5) +
  facet_wrap(~ year, ncol = 5, strip.position = "bottom") +
  theme_void() +
  theme(
    plot.title = element_text(hjust = 0.5, face = "bold", size = 14),
    strip.background = element_blank(),
    strip.text = element_text(size = 11, face = "italic", color = "gray20"),
    strip.placement = "outside",
    legend.position = "bottom",
    legend.direction = "horizontal",
    legend.title = element_blank(),
    legend.text = element_text(size = 9),
    legend.key.width = unit(1.2, "cm"),
    legend.key.height = unit(0.5, "cm")
  ) +
  scale_fill_manual(
    values = c(
      "3 White" = "#F0E442",
      "2 Hispanic" = "#D55E00",
      "1 Black" = "#0072B2",
      "5 Asian" = "#CC79A7",
      "4 Mixed" = "#009E73",
      "6 Black & Hispanic" = "#56B4E9"
    ),
    labels = c("Black", "Hispanic", "White", "Asian", "Mixed", "Black & Hispanic"),
    name = ""
  ) +

```

```

labs(
  title = "Racial Cluster Maps by Decade (1980-2020)",
  x = "", y = ""
) +
theme_void() +
theme(
  plot.title = element_text(hjust = 0.5, face = "bold", size = 14),
  legend.position = "bottom",
  legend.direction = "horizontal",
  legend.title = element_blank(),
  legend.text = element_text(size = 9),
  legend.key.width = unit(1.2, "cm"),
  legend.key.height = unit(0.5, "cm")
) +
guides(
  fill = guide_legend(nrow = 1, byrow = TRUE, label.position = "bottom")
)

```

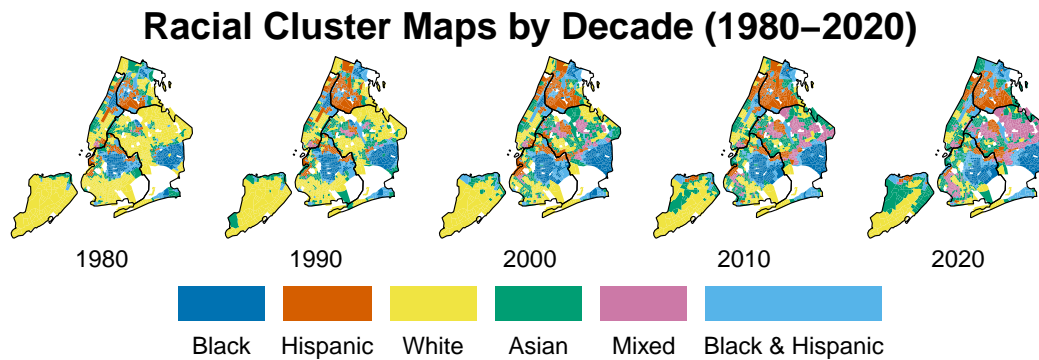


Figure 7: Change in the cluster membership over five decades

## Sequence Analysis

Our objective with the sequence classification is to come up with a typology of neighborhood sequences over time to describe general pathways of change. Each neighborhood has a sequence of classes over time, one of 6 categorical groups for each of the five decennial census values from 1980-2020. The first step in the analysis is to convert the data frame into a sequence for each neighborhood. We can see an illustrative example of the longitudinal sequences from the first five records. Classes are separated by a dash (-). There are 2122 sequences in the dataset and 197 unique sequences; all sequences are displayed in the plot below. Thus, the purpose of clustering the sequences is to extract the general patterns present from the set of all sequences.

```

# Convert the data from long to wide format to have a sequence for each neighborhood
# Assuming census_long is your data frame
census_wide <- tract_clusters_decades %>%
  st_drop_geometry() %>%
  select(TRTID10, year, label_6) %>%
  pivot_wider(names_from = year, values_from = label_6)

# Rename the columns to show only the year (remove "cluster_" prefix if it was added during
colnames(census_wide) <- sub("cluster_", "", colnames(census_wide))

# Ensure columns are in the correct order by year
census_wide <- census_wide %>%
  select(TRTID10, `1980`, `1990`, `2000`, `2010`, `2020`)

# Ensure the sequence columns are factors
census_wide <- census_wide %>%
  mutate(across(starts_with("19") | starts_with("20"), as.factor))

# Check the distinct states (categories) in your sequences
unique_states <- unique(unlist(census_wide[, -1])) # Exclude TRTID10 column
num_states <- length(unique_states)
print(unique_states)

```

```

[1] 6 Black & Hispanic 2 Hispanic          4 Mixed          3 White
[5] 1 Black          5 Asian
Levels: 1 Black 2 Hispanic 3 White 4 Mixed 5 Asian 6 Black & Hispanic

```

```

print(num_states) # Number of unique states

```

```

[1] 6

```

```

# Define the custom color palette with the correct colors
custom_palette <- c(
  "1 Black" = "#0072B2",
  "2 Hispanic" = "#D55E00",
  "3 White" = "#F0E442",
  "4 Mixed" = "#009E73",
  "5 Asian" = "#CC79A7",
  "6 Black and Hispanic" = "#56B4E9"
)

```

```
)

# Create the sequence object with the renamed columns
sequence_data <- seqdef(census_wide[, -1], cpal = custom_palette) # Exclude the TRTID10 c

# Check the number of distinct sequences
num_sequences <- seqtab(sequence_data, idx = 0) %>% nrow
print(num_sequences)
```

```
[1] 197
```

```
# Display the first few sequences
head(sequence_data)
```

Sequence

```
1 6 Black & Hispanic-2 Hispanic-6 Black & Hispanic-6 Black & Hispanic
2 2 Hispanic-2 Hispanic-2 Hispanic-2 Hispanic-2 Hispanic
3 2 Hispanic-2 Hispanic-2 Hispanic-2 Hispanic-2 Hispanic
4 2 Hispanic-2 Hispanic-2 Hispanic-2 Hispanic-2 Hispanic
5 2 Hispanic-2 Hispanic-2 Hispanic-2 Hispanic-2 Hispanic
6 4 Mixed-2 Hispanic-2 Hispanic-2 Hispanic-5 Asian
```

```
# Plot the sequences
seqIplot(sequence_data,                                     # Sequence object
          with.legend = "right",                             # Display legend on right s
          cex.legend = 0.6,                                   # Change size of legend
          main = "Neighborhood Racial and Ethnic Trajectories") # Plot title
```

## Neighborhood Racial and Ethnic Trajectory

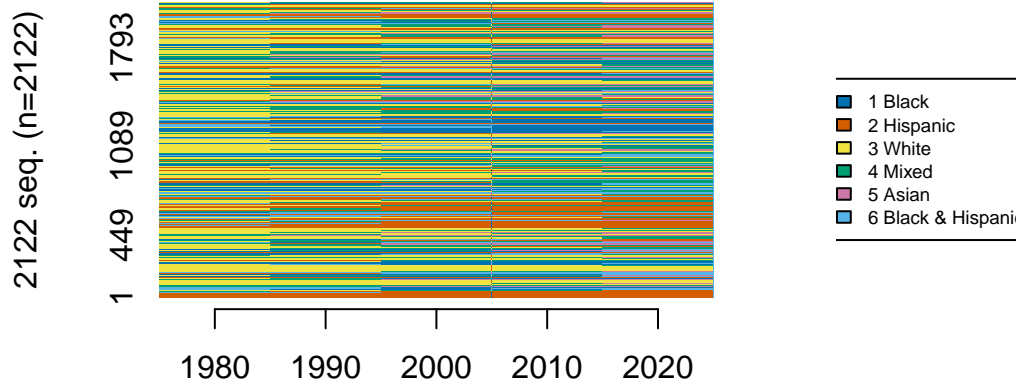


Figure 8: Sequence of each neighborhood.

The next objective is to compute the dissimilarity between all sequences. As described previously, we use the OMstrans algorithm to preserve the ordering of events as we are most interested in describing how neighborhoods have generally transitioned over time. We set a low value (0.1) for the parameter `otto` in the `seqdist` command which is the origin-transition trade-off weight. This emphasizes the ordering of sequence states. We also set a high `indel` cost of 3. Finally, substitution costs are a function of the transition rate `TRATE` between states. This places a lower cost on more frequent transitions.

The substitution cost matrix is shown in the Table below. The table indicates that more frequent transitions from, for example, Black & Hispanic to Black, Mixed to White, White to Mixed, and Black to Black and Hispanic have lower costs than rarer transitions from, for example, Asian to Black, Hispanic to Black, or Black to Asian. Generally, the more mixed race groups are more transitional while the majority race groups tend to transition through a mixed race state. This will become more evident as we examine the resulting sequence clusters.

Once the cost matrix is established, we then cluster the sequences using the dissimilarity matrix as an input to generate the typology. We follow an iterative process in determining the optimal solution like the one described above for the  $k$  means clustering. In short, multiple solutions are tested and the resulting sequence clusters are visualized to inspect for heterogeneity. Because our clustering and distance matrix are optimized for describing transitions over time, we end up with one cluster that contains all neighborhoods that remained constant over time. These sequences are very different from one another in the neighborhood types they describe, but they all represent a pathway or sequences of no change.

To describe the resulting sequence clusters, we plot a Sequence Frequency Plot for each cluster. We settled on 14 trajectory clusters describing neighborhood racial and ethnic transitions

from 1980 to 2020 in New York City. The Sequence Frequency Plots illustrate the sequences belonging to each cluster and the sequence bars are scaled to visualize the frequency of each sequence. A summary of the trajectories is as follows:

1. Hispanic Majority to Black & Hispanic
2. Stability Cluster
3. White & Mixed Race to Hispanic Majority
4. White to White & Mixed Race to Hispanic Majority
5. Black & Hispanic to Hispanic Majority
6. White Majority to White & Mixed Race
7. White & Mixed Race to Black & Hispanic
8. Black & Hispanic to Black Majority
9. White & Mixed Race to Asian Majority
10. White & Mixed Race to White Majority
11. Black & Hispanic to White & Mixed Race
12. White & Mixed Race to Asian Majority
13. Black Majority to Black & Hispanic
14. Black & Hispanic to Asian Majority

```
# Pass this palette to seqdef
# Define sequence data with custom color palette
sequence_data <- seqdef(census_wide[, -1], cpal = custom_palette) # Exclude the TRTID10 c

# Compute Optimal Matching (OM) distances using the TRATE cost method
costs <- seqcost(sequence_data, method = "TRATE")
om_distances <- seqdist(sequence_data, method = "OMstran", indel = 3, sm = costs$sm, otto

#Extract the substitution cost matrix
sub_matrix <- round(costs$sm, 2) # round to 2 decimal places for clarity

# Convert to a data frame for export
sub_df <- as.data.frame(sub_matrix)

# Add row names as a column for better display
sub_df$From <- rownames(sub_df)
sub_df <- sub_df[, c("From", setdiff(names(sub_df), "From"))]

# Optional: reorder columns to match row order
sub_df <- sub_df[, c("From", rownames(sub_matrix))]

# Print to console
print(sub_df)
```

		From 1 Black	2 Hispanic	3 White	4 Mixed
1 Black	1 Black	0.00	2.00	1.99	1.99
2 Hispanic	2 Hispanic	2.00	0.00	2.00	1.86
3 White	3 White	1.99	2.00	0.00	1.70
4 Mixed	4 Mixed	1.99	1.86	1.70	0.00
5 Asian	5 Asian	2.00	1.94	2.00	1.80
6 Black & Hispanic	6 Black & Hispanic	1.77	1.86	1.99	1.91
	5 Asian 6 Black & Hispanic				
1 Black	2.00	1.77			
2 Hispanic	1.94	1.86			
3 White	2.00	1.99			
4 Mixed	1.80	1.91			
5 Asian	0.00	1.97			
6 Black & Hispanic	1.97	0.00			

```
# Perform hierarchical clustering using Ward's method on the OM distances
clusterward <- agnes(om_distances, diss = TRUE, method = "ward")
```

```
# Define the number of clusters and assign clusters to the sequence data
num_clusters <- 14
clusters <- cutree(clusterward, k = num_clusters)
census_wide$sequence_cluster <- clusters
```

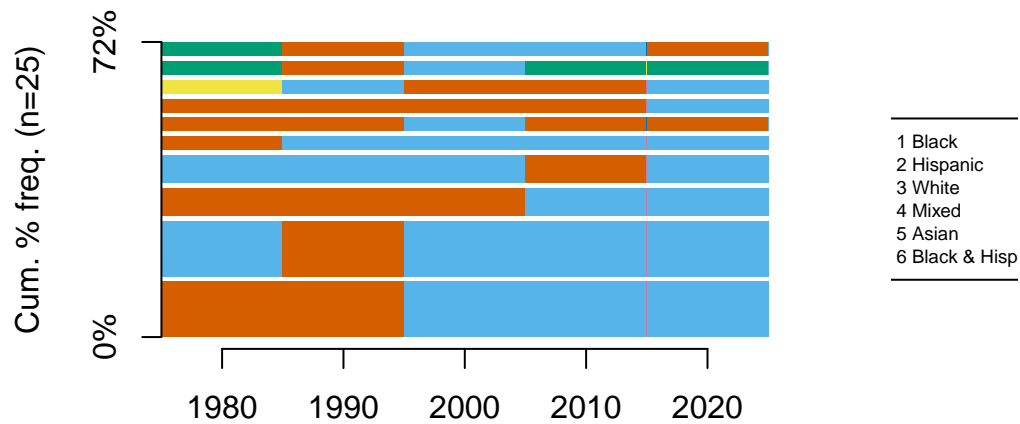
```
# Define all 14 cluster names
cluster_names_full <- c(
  "Hispanic Majority to Black & Hispanic",
  "Stability Cluster",
  "White & Mixed Race to Hispanic Majority",
  "White to White & Mixed Race to Hispanic Majority",
  "Black & Hispanic to Hispanic Majority",
  "White Majority to White & Mixed Race",
  "White & Mixed Race to Black & Hispanic",
  "Black & Hispanic to Black Majority",
  "White & Mixed Race to Asian Majority",
  "White & Mixed Race to White Majority",
  "Black & Hispanic to White & Mixed Race",
  "White & Mixed Race to Asian Majority",
  "Black Majority to Black & Hispanic",
  "Black & Hispanic to Asian Majority"
)
```



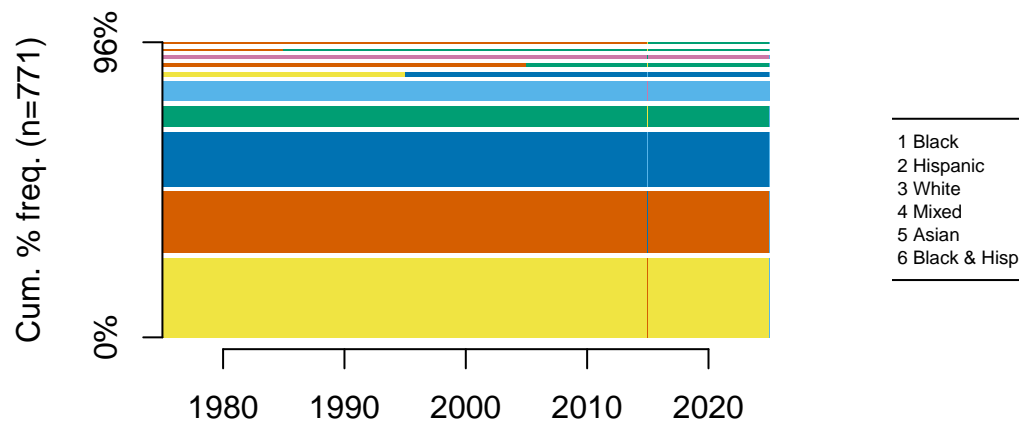
```
# Modified function that creates separate plots for each cluster in the range
plot_sequence_clusters <- function(cluster_range) {
  for(i in cluster_range) {
    seqfplot(
      sequence_data[census_wide$sequence_cluster == i, ],
      sortv = "from.start",
      border = NA,
      with.legend = "right",
      legend.prop = 0.2,
      legend.border = FALSE,
      main = paste("Cluster", i, ":", cluster_names_full[i]),
      cex.legend = 0.6 # Adjust this value: smaller = smaller text, larger = larger text
    )
  }
}

# Keep your existing calls - each will now create clean individual plots
plot_sequence_clusters(1:2) # Creates 2 separate plots with individual titles
```

### Cluster 1 : Hispanic Majority to Black & Hispanic

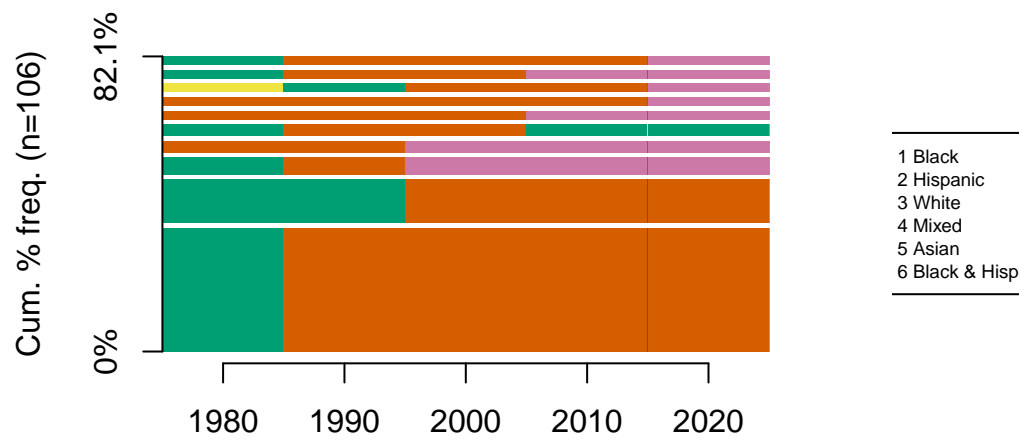


## Cluster 2 : Stability Cluster

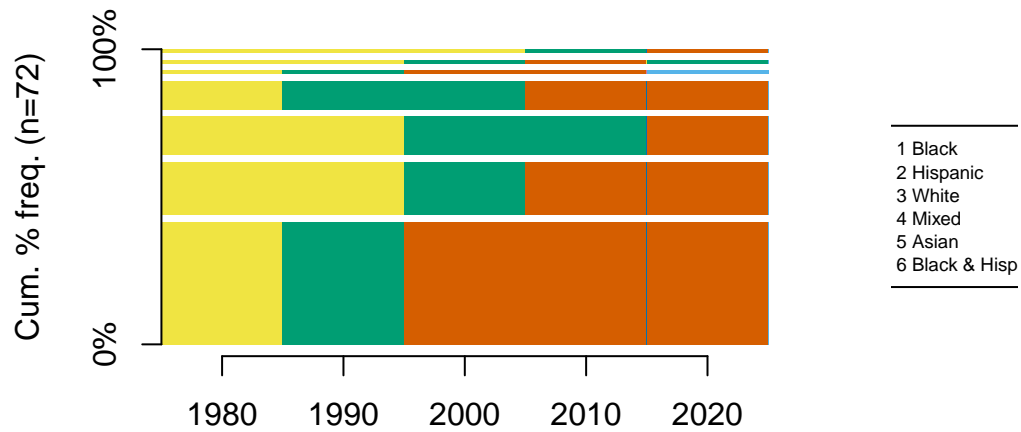


```
plot_sequence_clusters(3:4) # Creates 2 separate plots with individual titles
```

## Cluster 3 : White & Mixed Race to Hispanic Major

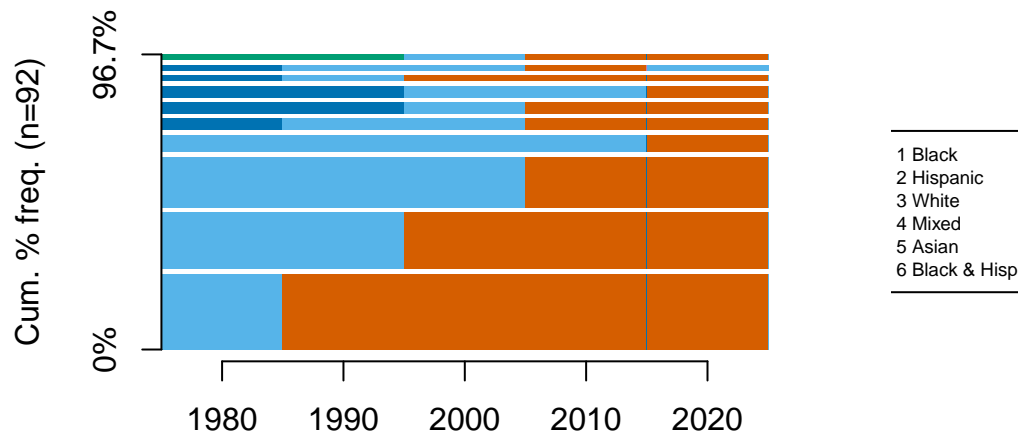


#### Cluster 4 : White to White & Mixed Race to Hispanic

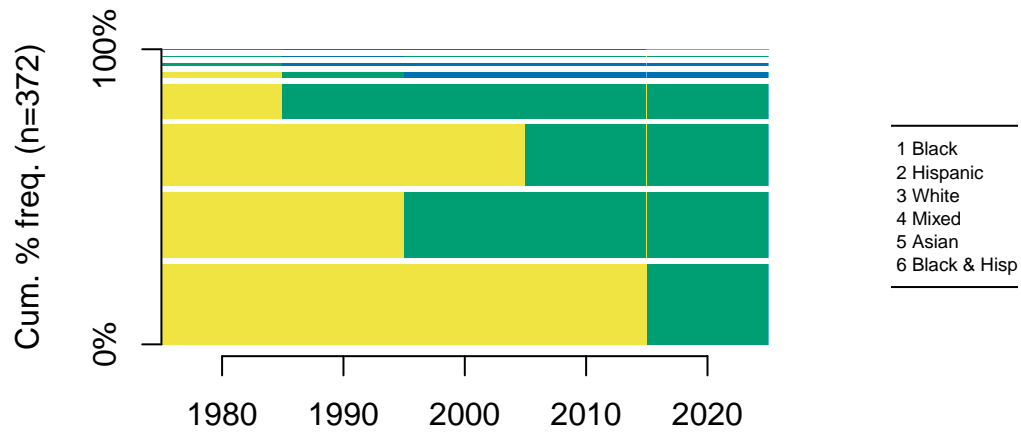


```
plot_sequence_clusters(5:6) # Creates 2 separate plots with individual titles
```

#### Cluster 5 : Black & Hispanic to Hispanic Major

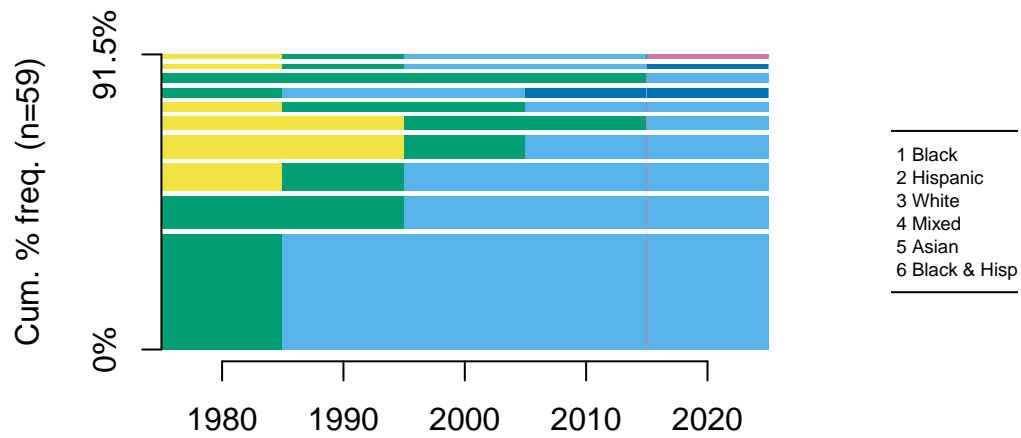


### Cluster 6 : White Majority to White & Mixed Ra

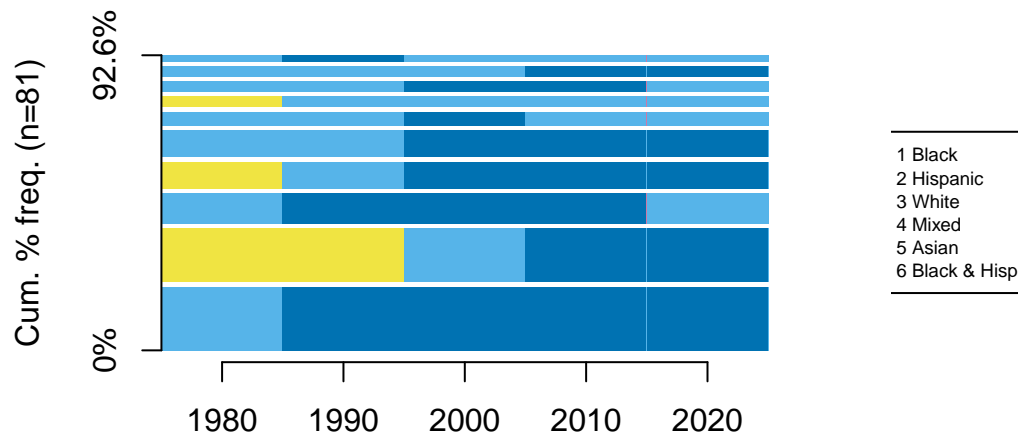


```
plot_sequence_clusters(7:8) # Creates 2 separate plots with individual titles
```

### Cluster 7 : White & Mixed Race to Black & Hisp

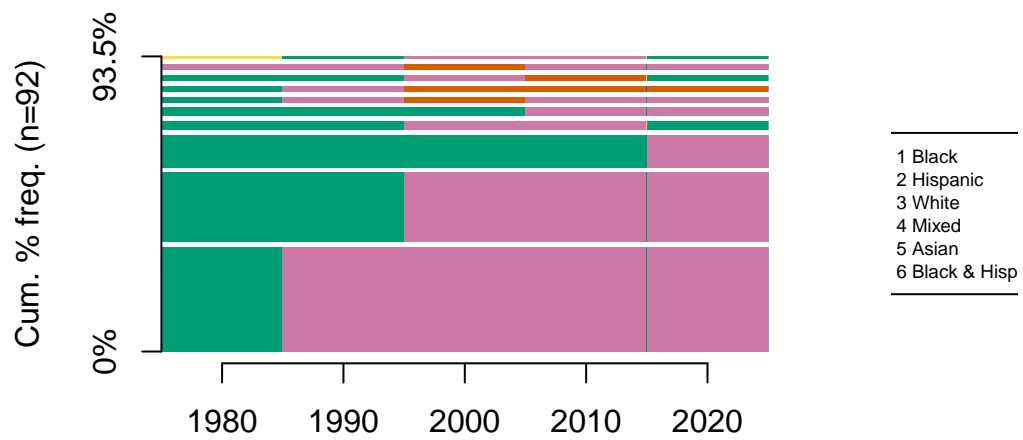


### Cluster 8 : Black & Hispanic to Black Majorit

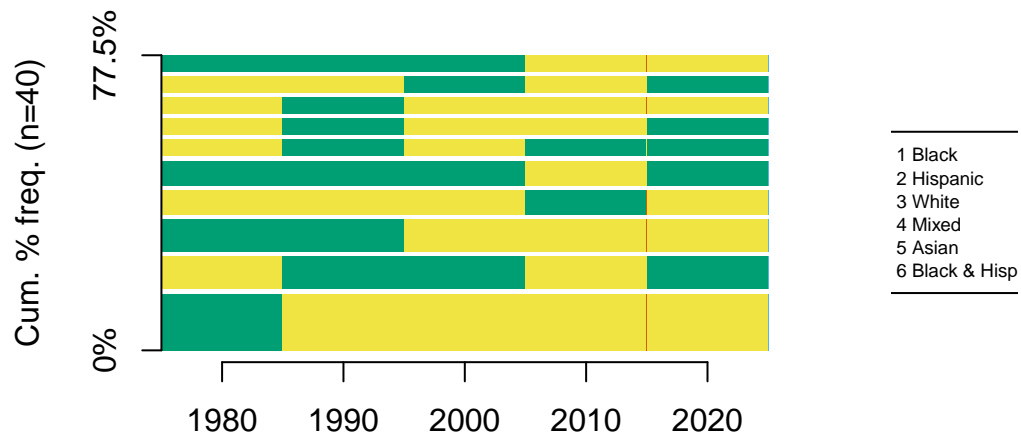


```
plot_sequence_clusters(9:10) # Creates 2 separate plots with individual titles
```

### Cluster 9 : White & Mixed Race to Asian Major

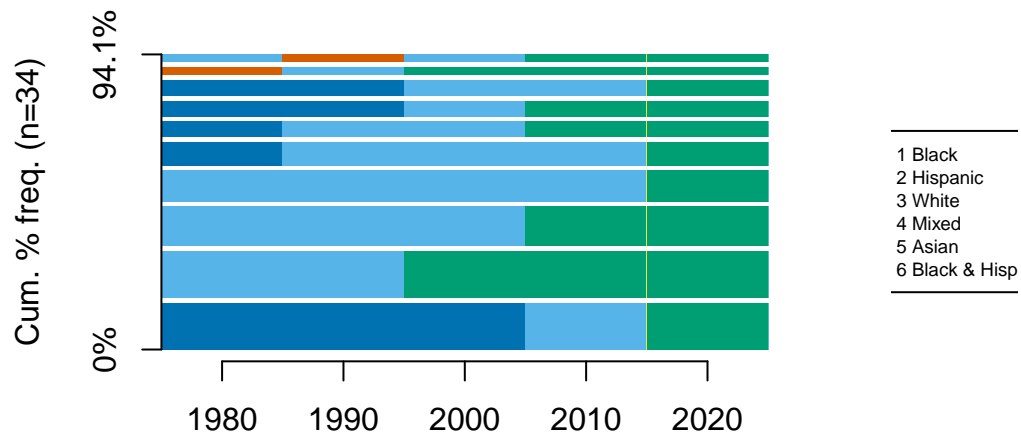


### Cluster 10 : White & Mixed Race to White Major

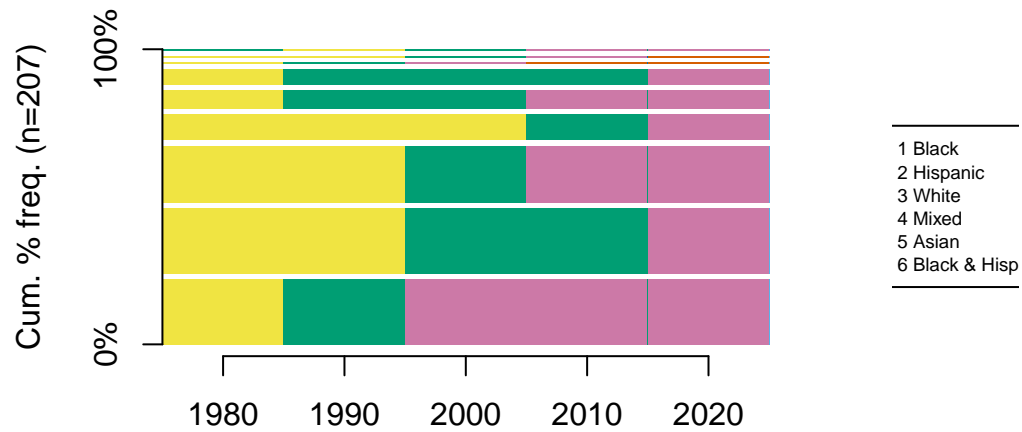


```
plot_sequence_clusters(11:12) # Creates 2 separate plots with individual titles
```

### Cluster 11 : Black & Hispanic to White & Mixed

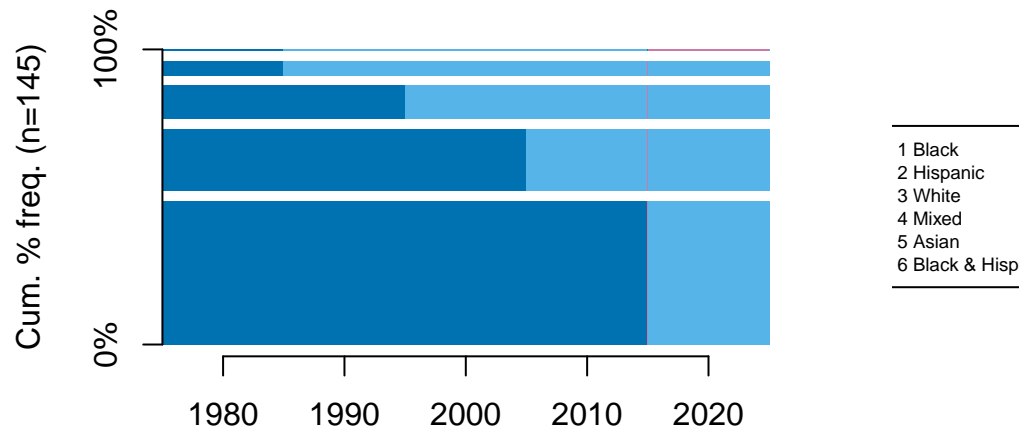


### Cluster 12 : White & Mixed Race to Asian Major

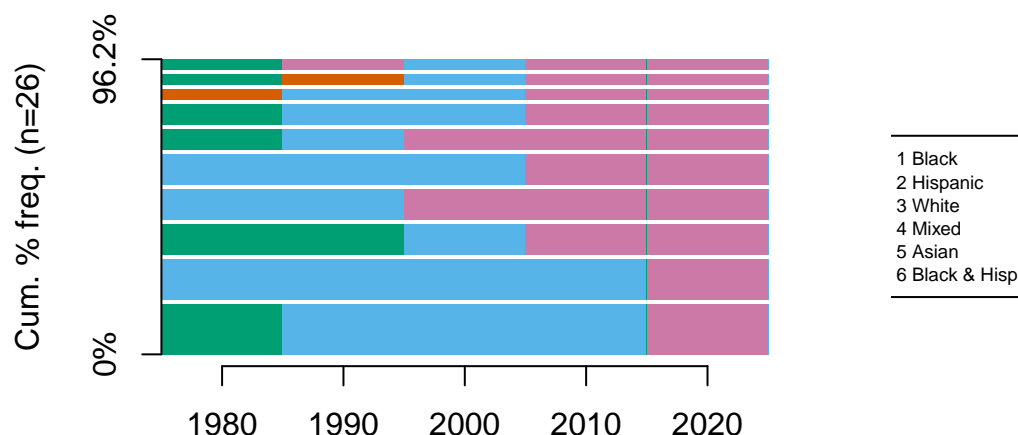


```
plot_sequence_clusters(13:14) # Creates 2 separate plots with individual titles
```

### Cluster 13 : Black Majority to Black & Hispanic



## Cluster 14 : Black & Hispanic to Asian Majority



Of these 14 pathways, there are 3 that lead to the formation of a neighborhood transitioning into a Hispanic Majority cluster by 2020. This includes Cluster 3 - showing neighborhoods that went from being a slight majority White, but with a mixture of other races in 1980 and 1990 to transitioning to majority Hispanic by 1990 or 2000. Some of these sequences indicate a continued transition towards becoming majority Asian in the later years. Further segmenting the sequences into more clusters may have separated out those trajectories, but for the sake of brevity, we leave them mixed in. Spatially, these are shown in orange on the map below and can be seen clustered in Staten Island, Queens, and in the Northern portion of the city. They are also notably adjacent to neighborhoods indicated by the red color, those representing sequence cluster 4, transitioning from majority White to White and Mixed Race and then to Majority Hispanic. This latter cluster might represent the precursor to cluster 3, but are neighborhoods that made this transition from majority White later, where the changes took time to spatially spillover to adjacent neighborhoods, as indicated by the map. Both of these pathways depict a transition from largely White populations to largely Hispanic.

The third pathway depicting a transition to majority Hispanic is distinct. It is represented by cluster 5 showing a transition from either majority Black neighborhoods towards a mixed Hispanic and Black group and eventually majority Hispanic or, beginning the 1980 time stamp, in a more mixed Black and Hispanic state. Geographically, these neighborhoods are shown more in the northern sections of Manhattan and the Bronx.

From these two sets of sequence clusters, we can see that majority Hispanic neighborhoods in New York City have emerged out of either majority Black or Majority White neighborhoods over time.

There are also 3 pathways leading to an Asian majority neighborhood type. These include clusters 9 and 12 which are also likely continuations of longer trajectories, that show a gradual transition from Majority White to White mixed race and eventually to Asian Majority. Geographically, these are clustered in the northern section of Queens. Sequence cluster 14 is more



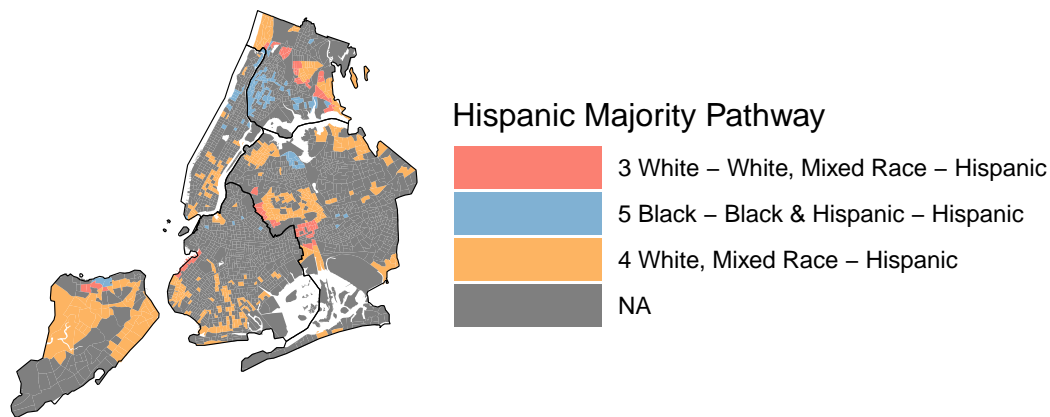


Figure 9: Neighborhoods Following Pathway to Hispanic Majority with White County Borders.

distinct in that the Asian majority transitioned from the Black and Hispanic mixed group and spatially, they are generally located in upper Manhattan and the Bronx.

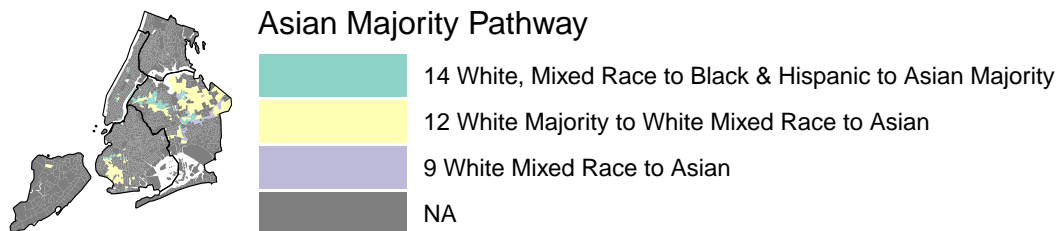


Figure 10: Neighborhoods Following Pathway to Asian Majority

```
# Filter data for Increasing White (clusters 10 and 11)
increasing_white_clusters <- census_wide %>%
  filter(sequence_cluster %in% c(10, 11)) # Clusters 10 and 11 for increasing White

# Filter data for Increasing Black (clusters 1 and 8)
increasing_black_clusters <- census_wide %>%
  filter(sequence_cluster %in% c(1, 8)) # Clusters 1 and 8 for increasing Black

# Join the filtered data with the tract shapefile for each group
tract_increasing_white <- tract %>% erase_water(area_threshold = 0.75) %>%
  left_join(increasing_white_clusters, by = "TRTID10") # Join spatial data for increasing
```

Fetching area water data for your dataset's location...

Erasing water area...

If this is slow, try a larger area threshold value.

```
tract_increasing_black <- tract %>%   erase_water(area_threshold = 0.75) %>%  
  left_join(increasing_black_clusters, by = "TRTID10") # Join spatial data for increasing
```

Fetching area water data for your dataset's location...

Erasing water area...

If this is slow, try a larger area threshold value.

There are two pathways for increasing both Black and White shares in a neighborhoods. Neighborhoods that became increasingly White either followed a trajectory from White mixed race to majority White (Cluster 10) or from either all Black or Black and Hispanic to White and Mixed race (11). Notably, this transition largely took place within the past 1-2 decades, aligning with when gentrification trends became accentuated in some cities, including New York. We see a clear cluster of this latter group in Brooklyn, a borough whose gentrification trends have been well documented (Chronopoulos 2020; Halasz 2023).

For the case of increasing Black populations, Cluster 1 shows a pathway from Hispanic majority to mixed Black and Hispanic and Cluster 8 shows a gradual transition from Black and Hispanic to majority Black; a trend that largely begin towards the middle of the study period, around the 2000 census data mark. Spatially, the former is more dispersed, while the latter is depicted more clearly in the southern neighborhoods of Brooklyn.

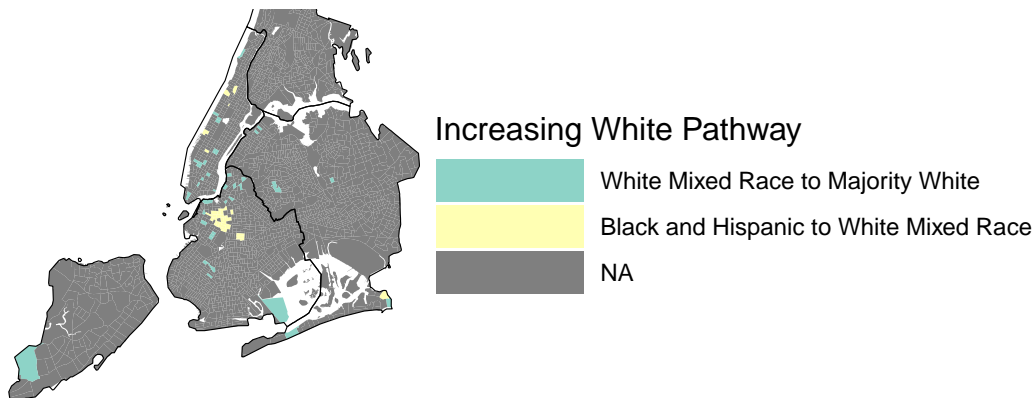


Figure 11: Neighborhoods Following Pathway to White Majority

Finally, of the sequences depicting no change from 1980 to 2020, shown in Cluster 2, the majority of those are for tracts with a racial majority: White, Hispanic, and Black. But those are followed by two stable sequences of neighborhoods with some racial diversity. The first is the majority White, but with a mixture of other races and the second is the mixed Black and Hispanic cluster. There is some debate in the literature whether racially mixed

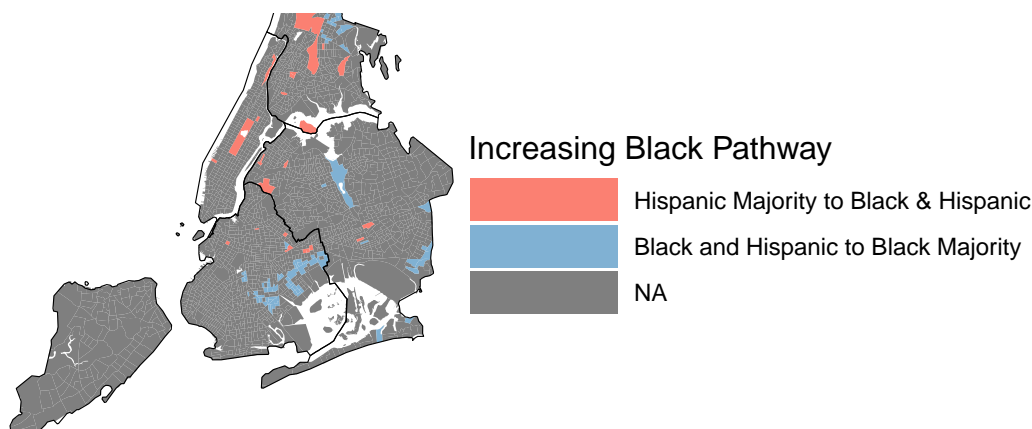


Figure 12: Neighborhoods Following Pathway to Black Majority

neighborhoods can be stable over time, or are they simply depicting a point along a pathway of change when one group will eventually become a majority. Research has shown that highly diverse neighborhoods are quite unstable over time, likely to transition to a less diverse state. In particular the transition from predominantly White towards majority Hispanic, results in a period of unstable racial mixture while that transition takes place (Wright et al. 2020). Others have identified a small, but persistent set of racially diverse neighborhoods throughout the United States, but particularly in racially diverse metropolitan areas (Hipp and Kim 2023b). Here, we find some evidence of stable, non-racially homogeneous Census Tracts.

## Conclusions

This analysis showcases a method for developing and visualizing a typology of neighborhood change pathways. We used a case study of decennial racial and ethnic changes in New York City census tracts from 1980-2020. The workflow first involves developing a cross-sectional typology of classes describing the racial mixture of neighborhoods. To do so, we used an unsupervised classification approach, *k*-means to derive six such clusters.

We demonstrated how determining the number of clusters often falls to more of an art than a precise science as our final clustering for this analysis exceeded the mathematically optimal three clusters, but provided us with more nuance on the racial mixture of neighborhoods. We performed the cluster analysis on all census tracts in the city for each of the five decennial census time stamps at once to ensure a temporally consistent set of groupings. We then created sequences of neighborhood clusters over the study period and developed a typology of sequences that grouped them based on the similarity of how they changed over time. To do so, we used the OMtrans algorithm for computing sequence dissimilarity to ensure that the ordering or sequencing of events was preserved. Finally, we mapped sequence clusters to spatially visualize neighborhoods that followed similar pathways of change. For our case study of the largest city

in the United States, and one of the most diverse, we observed a decline in the number of majority White census tracts over time. We identified several pathways of change leading to majority Hispanic neighborhoods - emerging either out of previously majority White or Black neighborhoods. We also observed pathways leading to majority Asian tracts, transitioning from Black and Hispanic neighborhoods, largely in Queens. A smaller share of neighborhoods became either increasingly White or Black. Neighborhoods that saw an increase in the share of Whites, saw a notable increase in the transition from Black and Hispanic to White and mixed race over the past two decades. Neighborhoods that increased in the share of Blacks largely transitioned from Black and Hispanic to majority Black or from White and mixed race to Black and Hispanic.

The strength of the sequence analysis technique lies in its ability to clearly visualize common pathways of neighborhood change. One of its limitations, however, is the need to segment continuous, longitudinal data into discrete, categorical states. In this article, we devoted attention to this step, illustrating the use of a  $k$ -means algorithm as an unsupervised classification method for grouping multiple variables. This phase involves decisions, particularly, the number of classes, as that directly influences the resulting sequences and subsequent interpretations. Alternative methods for clustering time series data that preserve the continuous nature of the data may be preferable in cases where the number of neighborhood variables is limited (Elizabeth C. Delmelle, Nilsson, and Duma 2025).

Beyond describing trajectories, sequence analysis also opens up avenues for further inquiry. The resulting sequence clusters can serve as the basis for additional analyses like modeling the predictors of specific trajectories or analyzing their spatial patterns using categorical spatial autocorrelation measures such as the join-count statistic.

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