Take-home\_Ex02

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# 1. Installing Packages and Importing Data

pacman::p\_load(tidyverse, jsonlite, SmartEDA, tidygraph,ggraph, igraph, lubridate, ggimage)

## 1.1 Read the Data

# Read JSON file  
mc1\_data <- fromJSON("data/MC1\_graph.json")

str(mc1\_data, max.level = 1)

List of 5  
 $ directed : logi TRUE  
 $ multigraph: logi TRUE  
 $ graph :List of 2  
 $ nodes :'data.frame': 17412 obs. of 10 variables:  
 $ links :'data.frame': 37857 obs. of 4 variables:

glimpse(mc1\_data)

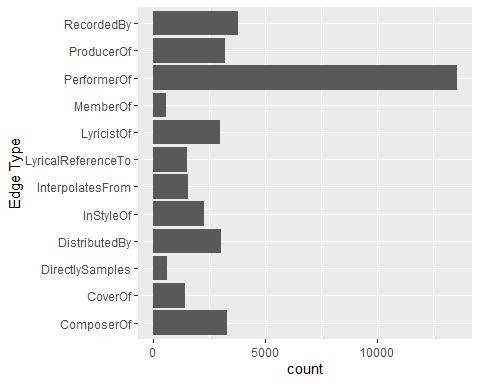
List of 5  
 $ directed : logi TRUE  
 $ multigraph: logi TRUE  
 $ graph :List of 2  
 ..$ node\_default: Named list()  
 ..$ edge\_default: Named list()  
 $ nodes :'data.frame': 17412 obs. of 10 variables:  
 ..$ Node Type : chr [1:17412] "Song" "Person" "Person" "Person" ...  
 ..$ name : chr [1:17412] "Breaking These Chains" "Carlos Duffy" "Min Qin" "Xiuying Xie" ...  
 ..$ single : logi [1:17412] TRUE NA NA NA NA FALSE ...  
 ..$ release\_date : chr [1:17412] "2017" NA NA NA ...  
 ..$ genre : chr [1:17412] "Oceanus Folk" NA NA NA ...  
 ..$ notable : logi [1:17412] TRUE NA NA NA NA TRUE ...  
 ..$ id : int [1:17412] 0 1 2 3 4 5 6 7 8 9 ...  
 ..$ written\_date : chr [1:17412] NA NA NA NA ...  
 ..$ stage\_name : chr [1:17412] NA NA NA NA ...  
 ..$ notoriety\_date: chr [1:17412] NA NA NA NA ...  
 $ links :'data.frame': 37857 obs. of 4 variables:  
 ..$ Edge Type: chr [1:37857] "InterpolatesFrom" "RecordedBy" "PerformerOf" "ComposerOf" ...  
 ..$ source : int [1:37857] 0 0 1 1 2 2 3 5 5 5 ...  
 ..$ target : int [1:37857] 1841 4 0 16180 0 16180 0 5088 14332 11677 ...  
 ..$ key : int [1:37857] 0 0 0 0 0 0 0 0 0 0 ...

## 1.2 Extract and inspect

nodes\_tbl <- as\_tibble(mc1\_data$nodes)  
edges\_tbl <- as\_tibble(mc1\_data$links)

## 1.3 Initial EDA

ggplot(data = edges\_tbl,  
 aes(y = `Edge Type`)) +   
 geom\_bar()



# 2. Creating Knowledge Graph

## Step 1. Mapping from node id to row index

id\_map <- tibble(id = nodes\_tbl$id,  
 index = seq\_len(  
 nrow(nodes\_tbl)))

This ensures each id from your node list is mapped to the correct row number.

## Step 2. Map Source and target IDs to row indices

edges\_tbl <- edges\_tbl %>%  
 left\_join(id\_map, by = c("source" = "id")) %>%  
 rename(from = index) %>%  
 left\_join(id\_map, by = c("target" = "id")) %>%  
 rename(to = index)

## Step 3. Remove N/A

edges\_tbl <- edges\_tbl %>%  
 filter(!is.na(from), !is.na(to))

## Step 4. Creating the graph

Lastly, tbl\_graph is used to create tidygraph’s graph object by using the code chunk below

graph <- tbl\_graph(nodes = nodes\_tbl,  
 edges = edges\_tbl,  
 directed = mc1\_data$directed)

## Step 5. Visualizing the knowledge graph

set.seed(1234)

# 2. Visualizing the whole graph

ggraph(graph, layout = "fr") +  
 geom\_edge\_link(alpha = 0.3,  
 colour = "gray") +  
 geom\_node\_point(aes(color = `Node Type`),  
 size = 4) +  
 geom\_node\_text(aes(label = name),  
 repel = TRUE,  
 size = 2.5) +  
 theme\_void()

Note: Plot the line first

## Step 1: Filter edges to only “Memberof”

graph\_memberof <- graph %>%  
 activate(edges) %>%  
 filter(`Edge Type` == "MemberOf")

## Step 2: Extract only connected nodes(i.e., used in thesee edges)

used\_nodes\_indices <- graph\_memberof %>%  
 activate(edges) %>%  
 as\_tibble() %>%  
 select(from, to) %>%  
 unlist() %>%  
 unique()

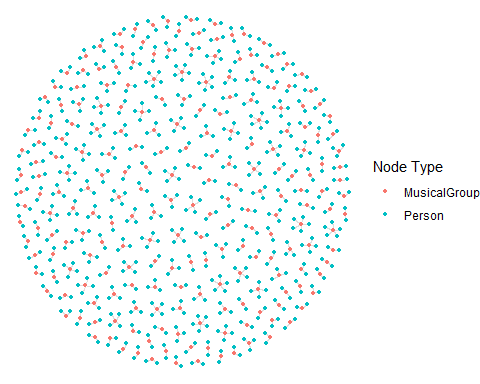
## Step 3: Keep only those nodes

graph\_memberof <- graph\_memberof %>%  
 activate(nodes) %>%  
 mutate(row\_id = row\_number()) %>%  
 filter(row\_id %in% used\_nodes\_indices) %>%  
 select(-row\_id)

## Plot the sub-graph

ggraph(graph\_memberof,  
 layout = "fr") +  
 geom\_edge\_link(alpha = 0.5,  
 colour = "gray") +  
 geom\_node\_point(aes(color = `Node Type`),  
 size = 1) +  
 geom\_node\_text(aes(label = name),  
 repel = TRUE,  
 size = 2.5) +  
 theme\_void()

Warning: ggrepel: 791 unlabeled data points (too many overlaps). Consider  
increasing max.overlaps



# 3. Background and Scenario - VAST Challenge Mini Case 1

One of music’s biggest superstars is Oceanus native Sailor Shift. From humble beginnings, Sailor has grown in popularity and now enjoys fans around the world. Sailor started her career on the island nation of Oceanus which can be clearly seen in her early work, she started in the genre of “Oceanus Folk”. While Sailor has moved away from the traditional Oceanus style, the Oceanus Folk has made a name for itself in the musical world. The popularity of this music is one of the factors driving an increase in tourism to a quiet island nation that used to be known for fishing.

In 2023, Sailor Shift joined the Ivy Echoes – an all-female Oceanus Folk band consisting of Sailor (vocalist), Maya Jensen (vocalist), Lila “Lilly” Hartman (guitarist), Jade Thompson (drummer), and Sophie Ramirez (bassist). They played together at venues throughout Oceanus but had broken up to pursue their individual careers by 2026. Sailor’s breakthrough came in 2028 when one of her singles went viral, launched to the top of the global charts (something no other Oceanus Folk song had ever done). Since then, she has only continued to grow in popularity worldwide.

Sailor has released a new album almost every year since her big break, and each has done better than the last. Although she has remained primarily a solo artist, she has also frequently collaborated with other established artists, especially in the Indie Pop and Indie Folk genres. She herself has branched out musically over the years but regularly returns to the Oceanus Folk genre — even as the genre’s influence on the rest of the music world has spread even more.

Sailor has always been passionate about two things: (1) spreading Oceanus Folk, and (2) helping lesser-known artists break into music. Because of those goals, she’s particularly famous for her frequent collaborations.

Additionally, because of Sailor’s success, more attention began to be paid over the years to her previous bandmates. All 4 have continued in the music industry—Maya as an independent vocalist, Lilly and Jade as instrumentalists in other bands, and Sophie as a music producer for a major record label. In various ways, all of them have contributed to the increased influence of Oceanus folk, resulting in a new generation of up-and-coming Oceanus Folk artists seeking to make a name for themselves in the music industry.

Now, as Sailor returns to Oceanus in 2040, a local journalist – Silas Reed – is writing a piece titled Oceanus Folk: Then-and-Now that aims to trace the rise of Sailor and the influence of Oceanus Folk on the rest of the music world. He has collected a large dataset of musical artists, producers, albums, songs, and influences and organized it into a knowledge graph. Your task is to help Silas create beautiful and informative visualizations of this data and uncover new and interesting information about Sailor’s past, her rise to stardom, and her influence.

# 4 Develop visualizations that illustrate how the influence of Oceanus Folk has spread through the musical world.

## 4.1 visualizing the popularity of Oceanus Folk songs

In this section, we are going to visualize the popularity of Oceanus Folk’s popularity by plotting the numbers of Oceanus Folk’s songs hitting the top chart.

### 4.1.1 Setting up annual statistics of the numbers of Oceanus Folk songs on the top chart

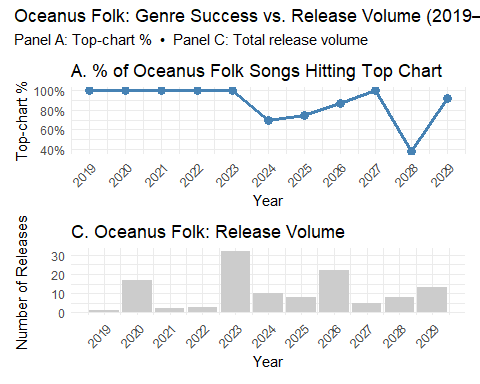
df <- nodes\_tbl %>%  
 filter(  
 `Node Type` == "Song",  
 genre == "Oceanus Folk",  
 !is.na(release\_date),  
 release\_date != ""  
 ) %>%  
 mutate(year = as.integer(release\_date)) %>%  
 filter(year > 2018, year < 2030) %>%  
 group\_by(year) %>%  
 summarise(  
 total = n(),  
 notable = sum(notable, na.rm = TRUE),  
 ratio = notable / total,  
 .groups = "drop"  
 ) %>%  
 arrange(year)

### 4.1.2 Plotting the graph

df\_ratio <- nodes\_tbl %>%  
 filter(  
 `Node Type` == "Song",  
 genre == "Oceanus Folk",  
 !is.na(release\_date),  
 release\_date != ""  
 ) %>%  
 mutate(year = as.integer(release\_date)) %>%  
 filter(year >= 2019, year <= 2029) %>%  
 group\_by(year) %>%  
 summarise(  
 total = n(),  
 notable = sum(notable, na.rm = TRUE),  
 ratio = notable / total,  
 .groups = "drop"  
 ) %>%  
 arrange(year)  
  
# ── 2) df\_counts: total Oceanus-Folk releases per year ─────────────────────  
df\_counts <- df\_ratio %>%  
 transmute(year, n\_releases = total)  
  
# ── 3) Plot Panels A & C ─────────────────────────────────────────────────  
  
# Panel A: Genre success rate  
p1 <- ggplot(df\_ratio, aes(x = year, y = ratio)) +  
 geom\_line(size = 1.2, color = "steelblue") +  
 geom\_point(size = 3, color = "steelblue") +  
 scale\_y\_continuous("Top-chart %", labels = scales::percent\_format(accuracy = 1)) +  
 scale\_x\_continuous("Year", breaks = df\_ratio$year) +  
 labs(title = "A. % of Oceanus Folk Songs Hitting Top Chart") +  
 theme\_minimal() +  
 theme(axis.text.x = element\_text(angle = 45, hjust = 1))

Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.  
ℹ Please use `linewidth` instead.

# Panel C: Total release volume  
p3 <- ggplot(df\_counts, aes(x = year, y = n\_releases)) +  
 geom\_col(fill = "gray80") +  
 scale\_y\_continuous("Number of Releases") +  
 scale\_x\_continuous("Year", breaks = df\_counts$year) +  
 labs(title = "C. Oceanus Folk: Release Volume") +  
 theme\_minimal() +  
 theme(axis.text.x = element\_text(angle = 45, hjust = 1))  
  
# ── 4) Combine panels vertically ──────────────────────────────────────────  
library(patchwork)  
  
(p1 / p3) +  
 plot\_annotation(  
 title = "Oceanus Folk: Genre Success vs. Release Volume (2019–2029)",  
 subtitle = "Panel A: Top-chart % • Panel C: Total release volume"  
 )



Perfect scores are fragile once the catalogue grows. – The genre maintained 100 % only while releases were scarce or strongly branded (early years, Ivy Echoes peak, curated 2027 wave).

Sailor’s presence is the single biggest swing factor. – When she pivots away (2028), the hit-rate collapses even though release volume is ordinary. – When she leads collaborations (2029) or headlines group projects (2023, 2026-27), success rates soar.

Volume alone doesn’t guarantee chart impact. – 2023 and 2026 had similar release surges, yet the hit-rate diverged (100 % vs ~86 %) depending on unified branding vs. fragmented efforts.

Strategic collaborations rejuvenate the scene. – The 2029 rebound aligns exactly with Sailor’s Roots & Tides initiative, confirming that leveraging star power to spotlight newcomers can lift an entire genre.

Bottom line: the data reinforce the article’s narrative that Oceanus Folk’s fortunes rise and fall with Sailor Shift’s artistic choices—especially her willingness to keep one foot in her roots while experimenting globally.

## 4.2 Visualizing the trend of popularity of Oceanus Folk.

### 4.2.1 Data Preparations - Naming the edges

edges2 <- edges\_tbl %>%  
 rename(rel\_type = `Edge Type`)

### 4.2.2 Filtering and Extracting the Data

oceanus\_edges <- edges2 %>%  
 semi\_join(  
 nodes\_tbl %>% filter(genre == "Oceanus Folk") %>% select(id),  
 by = c("target" = "id")  
 ) %>%  
 filter(rel\_type %in% c("ComposerOf", "PerformerOf", "ProducerOf"))  
  
df\_yearly <- oceanus\_edges %>%  
 left\_join(  
 nodes\_tbl %>% select(id, release\_date),  
 by = c("target" = "id")  
 ) %>%  
 mutate(  
 year = str\_extract(release\_date, "^\\d{4}") %>% as.integer()  
 ) %>%  
 filter(year >= 2022) %>%  
  
 group\_by(year, rel\_type) %>%  
 summarise(count = n(), .groups = "drop") %>%  
 pivot\_wider(  
 names\_from = rel\_type,  
 values\_from = count,  
 values\_fill = 0  
 ) %>%  
 arrange(year)

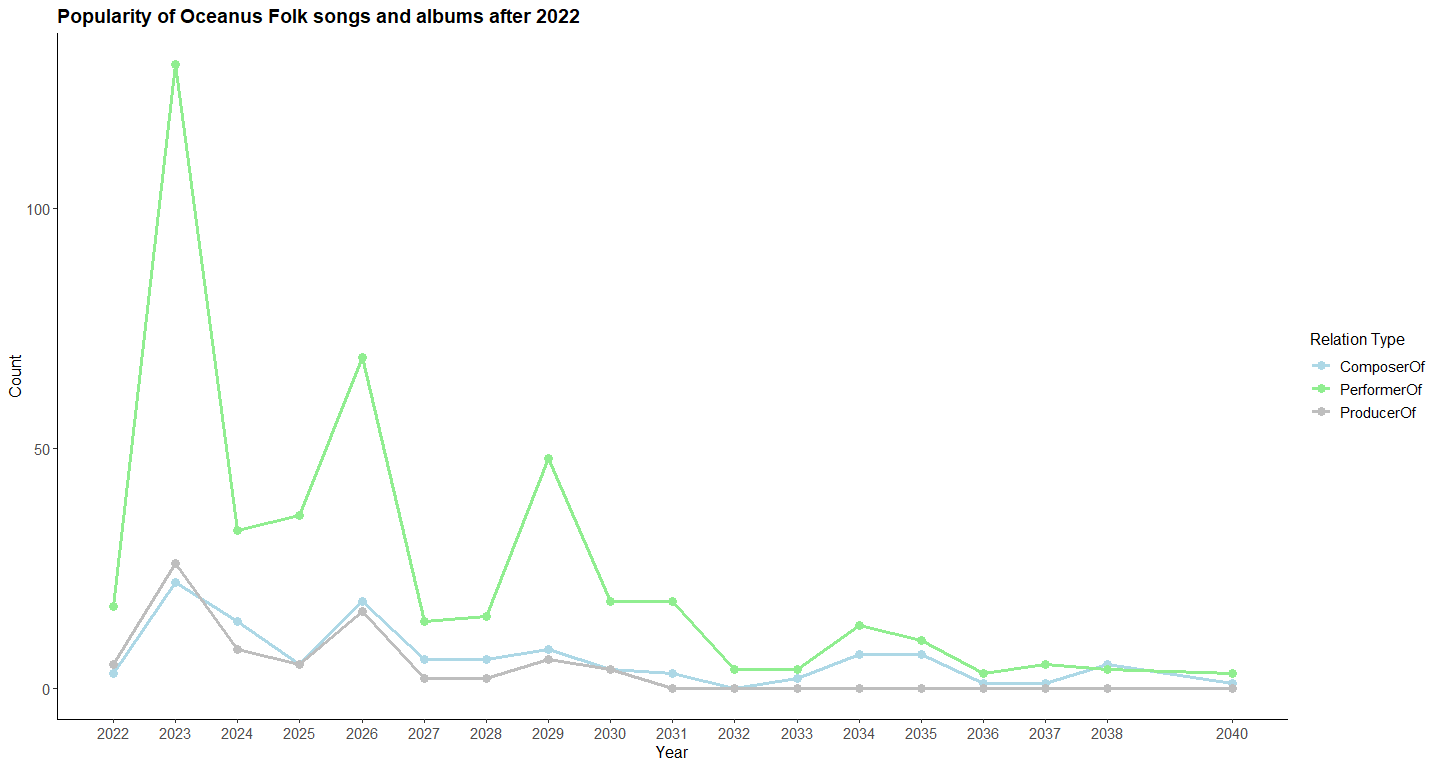
### 4.2.3 The data table

df\_yearly

# A tibble: 18 × 4  
 year ComposerOf PerformerOf ProducerOf  
 <int> <int> <int> <int>  
 1 2022 3 17 5  
 2 2023 22 130 26  
 3 2024 14 33 8  
 4 2025 5 36 5  
 5 2026 18 69 16  
 6 2027 6 14 2  
 7 2028 6 15 2  
 8 2029 8 48 6  
 9 2030 4 18 4  
10 2031 3 18 0  
11 2032 0 4 0  
12 2033 2 4 0  
13 2034 7 13 0  
14 2035 7 10 0  
15 2036 1 3 0  
16 2037 1 5 0  
17 2038 5 4 0  
18 2040 1 3 0

### 4.2.4 Plotting the line chart of the popularity of Oceanus Folk

df\_long <- df\_yearly %>%  
 pivot\_longer(  
 cols = c(ComposerOf, PerformerOf, ProducerOf),  
 names\_to = "rel\_type",  
 values\_to = "count"  
 )  
ggplot(df\_long, aes(x = year, y = count, color = rel\_type)) +  
 geom\_line(size = 1.2) +  
 geom\_point(size = 3) +  
 scale\_x\_continuous(breaks = df\_yearly$year) +  
 scale\_color\_manual(  
 name = "Relation Type",  
 values = c(  
 ComposerOf = "lightblue",   
 PerformerOf = "lightgreen",   
 ProducerOf = "gray"   
 )  
 ) +  
 labs(  
 title = "Popularity of Oceanus Folk songs and albums after 2022",  
 x = "Year",  
 y = "Count",  
 color = "Relation Type"  
 ) +  
 theme\_classic() +  
 theme(  
 plot.title = element\_text(size = 14, face = "bold"),  
 axis.title = element\_text(size = 12),  
 axis.text = element\_text(size = 11),  
 legend.title = element\_text(size = 12),  
 legend.text = element\_text(size = 11)  
 )



Big picture Three distinct “Sailor pulses.” Performer spikes (2023, 2026, 2029) align exactly with:

the Ivy Echoes boom,

their farewell, and

Sailor’s Roots & Tides comeback. Each pulse corresponds to a rebound or preservation of the 100 % (or near-perfect) top-chart ratio on the first graph.

Quality vs. quantity hinges on unified branding. When large output is driven by a cohesive banner (Ivy Echoes, Roots & Tides), the genre keeps its hit-making reputation. When volume grows without Sailor’s direct stamp (mid-2020s), success rates slip.

Post-2030 fade shows influence isn’t permanent without stewardship. Composer and producer lines outlive performer activity—reflecting Maya’s writing gigs and Sophie’s studio career—but neither is enough to maintain mainstream traction. The genre becomes boutique again until Sailor’s 2040 homecoming.

Silas Reed’s editorial angle. These intertwined trajectories visually prove his thesis: Oceanus Folk’s rise, dips, and mini-revivals are inseparable from Sailor Shift’s career choices—whether she’s front-stage, curating collaborations, or momentarily absent from the scene.

Use the two visuals together in the article:

Figure 1 (2019-29 panels) to show the front-end outcomes—chart success and release volume.

Figure 2 (role-based 2022-40 plot) to uncover the back-end mechanics—who is writing, performing, producing, and how that ebbs when Sailor steps away.

# 5. Examining the most influenced artist and genre of music by Visualizing the influence graph

## 5.1 Visualizing the influence Graph - The genre of music most influenced by Oceanus Folk

### 5.1.1 Defining the influence types

influence\_types <- c(  
 "CoverOf",  
 "InStyleOf",  
 "DirectlySamples",  
 "InterpolatesFrom",  
 "LyricalReferenceTo"  
)  
edges2 <- edges\_tbl %>% rename(rel\_type = `Edge Type`)

### 5.1.2 Filtering the Data

# 1.1 Extracting   
direct\_edges <- edges2 %>%  
 filter(rel\_type %in% influence\_types) %>%  
 semi\_join(  
 nodes\_tbl %>% filter(`Node Type` == "Song", genre == "Oceanus Folk") %>% select(id),  
 by = c("target" = "id")  
 )

### 5.1.3 Filtering the songs that are influenced by Oceanus Folks but do not belongs to Oceanus Folk

direct\_songs <- nodes\_tbl %>%  
 filter(  
 id %in% direct\_edges$source,  
 `Node Type` == "Song",  
 genre != "Oceanus Folk"  
 ) %>%  
 select(song\_id = id, song\_name = name, release\_date, genre)  
artist\_songs <- edges2 %>%  
 filter(rel\_type == "PerformerOf") %>%  
 semi\_join(  
 nodes\_tbl %>% filter(name %in% c("Sailor Shift", "Ivy Echoes")) %>% select(id),  
 by = c("source" = "id")  
 ) %>%  
 pull(target) %>%  
 unique() %>%  
 { nodes\_tbl %>%  
 filter(  
 id %in% .,  
 `Node Type` == "Song",  
 genre != "Oceanus Folk"  
 ) %>%  
 select(song\_id = id, song\_name = name, release\_date, genre)  
 }

### 5.1.4 Combine the data

step1\_songs <- bind\_rows(direct\_songs, artist\_songs) %>%  
 distinct(song\_id, song\_name, release\_date, genre)  
step1\_songs

# A tibble: 109 × 4  
 song\_id song\_name release\_date genre   
 <int> <chr> <chr> <chr>   
 1 196 Radiant Dreams 2017 Indie Folk   
 2 925 Liminal Passage 2027 Indie Folk   
 3 1069 Behind the Picture Glass 2026 Synthwave   
 4 1313 Radiance of the Heart 2029 Synthwave   
 5 1629 Legionary's Lament 2023 Desert Rock   
 6 1874 Dusty Miles 2023 Dream Pop   
 7 2260 Inherited Arguments 2029 Symphonic Metal  
 8 2272 Borrowed Time 2022 Space Rock   
 9 2379 Unwanted (And Still Waiting) 2027 Synthpop   
10 3053 Dreaming in Technicolor 2024 Desert Rock   
# ℹ 99 more rows

second\_edges <- edges2 %>%  
 filter(rel\_type %in% influence\_types) %>%  
 semi\_join(  
 step1\_songs %>% select(id = song\_id),  
 by = c("target" = "id")  
 )  
  
step2\_songs <- nodes\_tbl %>%  
 filter(  
 id %in% second\_edges$source,  
 `Node Type` == "Song",  
 genre != "Oceanus Folk"  
 ) %>%  
 select(song\_id = id, song\_name = name, release\_date, genre) %>%  
 distinct()  
step2\_songs

# A tibble: 70 × 4  
 song\_id song\_name release\_date genre   
 <int> <chr> <chr> <chr>   
 1 210 Luminous Path 2029 Darkwave   
 2 321 Soil of My Soul 2025 Space Rock  
 3 901 Approaching Silhouettes 2029 Space Rock  
 4 1076 Snapshot Shadows 2025 Dream Pop   
 5 1358 If Freedom Were an Open Door 2027 Dream Pop   
 6 1970 Footsteps in the Forest's Embrace 2027 Darkwave   
 7 3358 Carry Me Through 2017 Dream Pop   
 8 3580 Shadows of Unexpressed Feelings 2027 Dream Pop   
 9 3652 Wishful Thinking Anthem 2025 Dream Pop   
10 4085 Balcony Heartbreak 2023 Indie Folk  
# ℹ 60 more rows

infl\_edges <- edges\_tbl %>%  
 rename(rel\_type = `Edge Type`) %>%  
 filter(rel\_type %in% influence\_types)

## 5.2 Visualizing the level of influences by Oceanus Folk of all genres of music

### 5.2.1 Extracting the data of genre of songs and album

infl\_genre <- infl\_edges %>%  
 left\_join(  
 nodes\_tbl %>% select(id, genre),  
 by = c("target" = "id")  
 ) %>%  
 filter(!is.na(genre))

### 5.2.2 Grouping the data by *Genre* and *rel\_tyoe*

genre\_influence\_counts <- infl\_genre %>%  
 group\_by(genre, rel\_type) %>%  
 summarise(count = n(), .groups = "drop") %>%  
 pivot\_wider(  
 names\_from = rel\_type,  
 values\_from = count,  
 values\_fill = 0  
 ) %>%  
 arrange(genre)  
genre\_influence\_counts

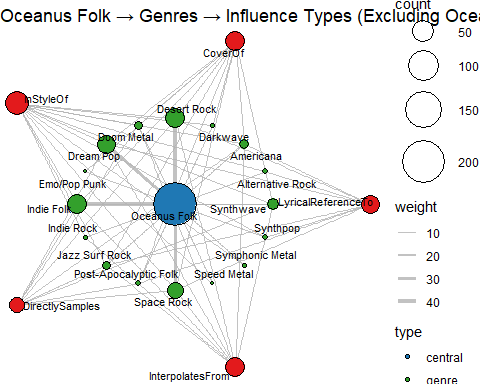
# A tibble: 24 × 6  
 genre CoverOf DirectlySamples InStyleOf InterpolatesFrom LyricalReferenceTo  
 <chr> <int> <int> <int> <int> <int>  
 1 Altern… 53 22 87 67 75  
 2 Americ… 29 13 62 39 43  
 3 Avant-… 29 16 47 28 33  
 4 Blues … 26 9 44 39 33  
 5 Celtic… 0 0 0 0 1  
 6 Darkwa… 27 19 47 30 28  
 7 Desert… 19 9 35 35 20  
 8 Doom M… 156 83 270 178 165  
 9 Dream … 168 77 245 188 168  
10 Emo/Po… 45 18 71 37 42  
# ℹ 14 more rows

### 5.2.3 Defining the Edges and Nodes

edges2 <- edges\_tbl %>% rename(rel\_type = `Edge Type`)  
  
genre\_counts <- edges2 %>%  
 filter(rel\_type %in% influence\_types) %>%  
 semi\_join(  
 nodes\_tbl %>% filter(`Node Type` == "Song", genre == "Oceanus Folk") %>% select(id),  
 by = c("target"="id")  
 ) %>%  
 left\_join(nodes\_tbl %>% select(id, genre), by = c("source"="id")) %>%  
 filter(!is.na(genre)) %>%  
 group\_by(genre, rel\_type) %>%  
 summarise(n = n(), .groups="drop") %>%  
 pivot\_wider(names\_from = rel\_type, values\_from = n, values\_fill = 0) %>%  
 filter(genre != "Oceanus Folk") %>%  
 mutate(total\_genre = rowSums(select(., all\_of(influence\_types))))  
  
rel\_totals <- colSums(select(genre\_counts, all\_of(influence\_types)))  
  
# Defining the Nodes  
nodes <- bind\_rows(  
 tibble(id = "Oceanus Folk", type = "central", count = sum(genre\_counts$total\_genre)),  
 tibble(id = genre\_counts$genre, type = "genre", count = genre\_counts$total\_genre),  
 tibble(id = influence\_types, type = "reltype", count = as.integer(rel\_totals))  
)  
edges1 <- tibble(  
 from = "Oceanus Folk",  
 to = genre\_counts$genre,  
 weight = genre\_counts$total\_genre  
)  
edges2 <- genre\_counts %>%  
 pivot\_longer(all\_of(influence\_types), names\_to="to", values\_to="weight") %>%  
 filter(weight>0) %>%  
 transmute(from = genre, to = to, weight = weight)  
  
edges <- bind\_rows(edges1, edges2)

### 5.2.4 Plotting the graph

graph\_plot <- tbl\_graph(nodes, edges, directed = FALSE)  
  
genres <- nodes %>% filter(type=="genre") %>% pull(id)  
rels <- nodes %>% filter(type=="reltype")%>% pull(id)  
ang\_g <- seq(0, 2\*pi, length.out=length(genres)+1)[-1]  
ang\_r <- seq(0, 2\*pi, length.out=length(rels)+1)[-1]  
layout <- tibble(  
 id = c("Oceanus Folk", genres, rels),  
 x = c(0, cos(ang\_g), 2\*cos(ang\_r)),  
 y = c(0, sin(ang\_g), 2\*sin(ang\_r))  
)  
  
l <- create\_layout(graph\_plot, layout="manual", x=layout$x, y=layout$y)  
  
ggraph(l) +  
 geom\_edge\_link(aes(width=weight), color="grey70", alpha=0.8) +  
 scale\_edge\_width(range=c(0.2,1.5)) +  
 geom\_node\_point(aes(size=count, fill=type), shape=21, color="black") +  
 scale\_size\_area(max\_size=15) +  
 scale\_fill\_manual(values=c(central="#1f78b4", genre="#33a02c", reltype="#e31a1c")) +  
 geom\_node\_text(aes(label=id), repel=TRUE, size=3) +  
 theme\_void() +  
 labs(title="Oceanus Folk → Genres → Influence Types (Excluding Oceanus Folk)")



Connecting all three visuals (timelines + role-plot + influence-network) Chart dominance ↔ thick influence spokes. 2019-23 and 2029 show both high hit-rates and vigorous multi-genre edges (especially Cover / InStyleOf). 2028 dip = thin performer/composer counts and (in the knowledge graph) fewer new outward edges.

Role diversity precedes genre diffusion. The 2026 farewell spike sees composer and producer nodes busy → graph shows wider CoverOf edges the following year (artists re-working Ivy Echoes catalog).

Stewardship matters. After Sailor’s focus shifts in the early 2030s, performer/composer lines flatten, and here we see few thick new edges—Oceanus Folk’s brokerage power wanes until her 2040 homecoming.

Additional clues from the influence-types Re-interpretation over raw sampling – InStyleOf, CoverOf, and InterpolatesFrom account for most heavy edges, whereas DirectlySamples has the thinnest fan-out. Oceanus Folk is being re-performed and referenced far more than it is sampled.

Story-telling travels as lyrics – the right-hand red node LyricalReferenceTo links Oceanus Folk to Alt-Rock and Synthwave, underscoring that even when the acoustic sound is left behind, the maritime imagery and narrative structure live on.

The genres soaking up Oceanus Folk influence most heavily are Desert Rock and Doom Metal, followed by the more predictable Indie Folk and crossover styles like Dream Pop and Synthwave. Musicians in those scenes aren’t grabbing raw samples; instead, they cover, reinterpret, or insert folk chord-loops and sea-faring lyrics into their own soundscapes. That pattern reinforces Oceanus Folk’s role as a story-telling blueprint rather than a beat library.

## 5.2 Visualzing the most influenced artist by Oceanus Folk

### 5.2.1 Defining the Edges

edges2 <- edges\_tbl %>% rename(rel\_type = `Edge Type`)

### 5.2.3 Filtering the Oceanus Folk songs

oceanus\_song\_ids <- nodes\_tbl %>%  
 filter(`Node Type` == "Song", genre == "Oceanus Folk") %>%  
 pull(id)  
  
step1\_song\_ids <- edges2 %>%  
 filter(rel\_type %in% influence\_types, target %in% oceanus\_song\_ids) %>%  
 pull(source) %>%  
 unique()

### 5.2.4 Filtering the songs influenced by the Oceanus songs

step2\_song\_ids <- edges2 %>%  
 filter(rel\_type %in% influence\_types, target %in% step1\_song\_ids) %>%  
 pull(source) %>%  
 unique()

### 5.2.5 Combining the songs influenced by Oceanus Folks

# 5. 合并所有受影响的歌曲 ID  
all\_song\_ids <- unique(c(step1\_song\_ids, step2\_song\_ids))  
  
# 6. 统计演唱者（包括 Person 和 MusicalGroup），排除姓名 NA  
performer\_counts <- edges2 %>%  
 filter(rel\_type == "PerformerOf", target %in% all\_song\_ids) %>%  
 count(source, name = "song\_count") %>%  
 rename(performer\_id = source) %>%  
 left\_join(  
 nodes\_tbl %>%  
 filter(`Node Type` %in% c("Person", "MusicalGroup")) %>%  
 select(performer\_id = id, performer = name),  
 by = "performer\_id"  
 ) %>%  
 filter(!is.na(performer))

### 5.2.6 Listing the top 5 artist influenced by Oceanus Folk

top5 <- performer\_counts %>%  
 slice\_max(song\_count, n = 5)  
top5

# A tibble: 7 × 3  
 performer\_id song\_count performer   
 <int> <int> <chr>   
1 2006 5 Filippo Pelli  
2 1180 4 Guiying Liao   
3 1182 4 Yan Zou   
4 1492 4 Juan Yu   
5 1493 4 Lei Jin   
6 4394 4 Xiuying Li   
7 4395 4 Xia Cui

### 5.2.7 Defining the types of influence and Edges

influence\_types <- c(  
 "CoverOf", "InStyleOf", "DirectlySamples",  
 "InterpolatesFrom", "LyricalReferenceTo"  
)  
edges2 <- edges\_tbl %>% rename(rel\_type = `Edge Type`)  
of\_song\_ids <- nodes\_tbl %>%  
 filter(`Node Type` == "Song", genre == "Oceanus Folk") %>%  
 pull(id)

### 5.2.8 Filtering and Listing the songs ID influenced by Oceanus Folk

step1\_song\_ids <- edges2 %>%  
 filter(rel\_type %in% influence\_types, target %in% of\_song\_ids) %>%  
 pull(source) %>% unique()  
  
step2\_song\_ids <- edges2 %>%  
 filter(rel\_type %in% influence\_types, target %in% step1\_song\_ids) %>%  
 pull(source) %>% unique()  
  
all\_song\_ids <- unique(c(step1\_song\_ids, step2\_song\_ids))

## 5.3 Calculating the times of these singers performing inf;uenced songs

### 5.3.1 Defining the Edges

direct\_edges <- edges2 %>%  
 filter(rel\_type %in% influence\_types, target %in% of\_song\_ids) %>%  
 transmute(influenced\_song\_id = source, influence\_type = rel\_type)  
  
second\_edges <- edges2 %>%  
 filter(rel\_type %in% influence\_types, target %in% step1\_song\_ids) %>%  
 transmute(influenced\_song\_id = source, influence\_type = rel\_type)  
  
all\_influence\_edges <- bind\_rows(direct\_edges, second\_edges)

### 5.3.2 Collecting the influeced songs performed by Top 5 artist

performer\_edges <- edges2 %>%  
 filter(  
 rel\_type == "PerformerOf",  
 source %in% top5$performer\_id,  
 target %in% all\_song\_ids  
 ) %>%  
 transmute(performer\_id = source, song\_id = target)  
  
table\_top5 <- performer\_edges %>%  
 left\_join(top5 %>% select(performer\_id, performer), by = "performer\_id") %>%  
 left\_join(all\_influence\_edges, by = c("song\_id" = "influenced\_song\_id")) %>%  
 left\_join(  
 nodes\_tbl %>% select(id, name, `Node Type`),  
 by = c("song\_id" = "id")  
 ) %>%  
 select(  
 performer,  
 song\_or\_album = name,  
 node\_type = `Node Type`,  
 influence\_type  
 ) %>%  
 arrange(performer, song\_or\_album)

Warning in left\_join(., all\_influence\_edges, by = c(song\_id = "influenced\_song\_id")): Detected an unexpected many-to-many relationship between `x` and `y`.  
ℹ Row 1 of `x` matches multiple rows in `y`.  
ℹ Row 12 of `y` matches multiple rows in `x`.  
ℹ If a many-to-many relationship is expected, set `relationship =  
 "many-to-many"` to silence this warning.

### 5.3.3 Summary Table

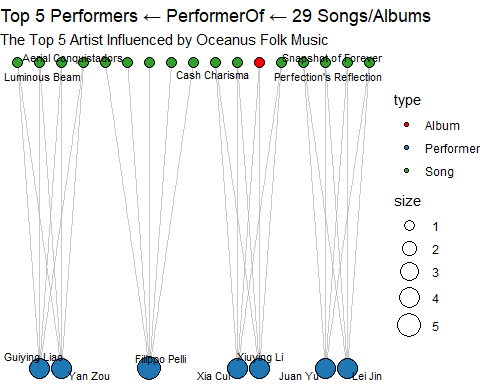
table\_top5

# A tibble: 82 × 4  
 performer song\_or\_album node\_type influence\_type   
 <chr> <chr> <chr> <chr>   
 1 Filippo Pelli Carry Me Through Song CoverOf   
 2 Filippo Pelli Carry Me Through Song InStyleOf   
 3 Filippo Pelli Carry Me Through Song CoverOf   
 4 Filippo Pelli Carry Me Through Song InStyleOf   
 5 Filippo Pelli Glance My Way Song InStyleOf   
 6 Filippo Pelli Lonesome Trail Ballad Song CoverOf   
 7 Filippo Pelli Roadside Memories Song CoverOf   
 8 Filippo Pelli Welcome to the Kemono Sanctuary Song LyricalReferenceTo  
 9 Guiying Liao Aerial Conquistadors Song InterpolatesFrom   
10 Guiying Liao Aerial Conquistadors Song InterpolatesFrom   
# ℹ 72 more rows

### 5.3.4 Plotting the Graph

influence\_types <- c(  
 "LyricistOf","RecordedBy","DistributedBy",  
 "InStyleOf","InterpolatesFrom","CoverOf",  
 "LyricalReferenceTo","DirectlySamples"  
)  
edges2 <- edges\_tbl %>% rename(rel\_type = `Edge Type`)  
  
# 2. Oceanus Folk 的 Song ID  
of\_song\_ids <- nodes\_tbl %>%  
 filter(`Node Type`=="Song", genre=="Oceanus Folk") %>%  
 pull(id)  
  
step1 <- edges2 %>%  
 filter(rel\_type %in% influence\_types, target %in% of\_song\_ids) %>%  
 pull(source) %>% unique()  
step2 <- edges2 %>%  
 filter(rel\_type %in% influence\_types, target %in% step1) %>%  
 pull(source) %>% unique()  
all\_songs <- unique(c(step1, step2))  
  
performer\_counts <- edges2 %>%  
 filter(rel\_type=="PerformerOf", target %in% all\_songs) %>%  
 count(source, name="song\_count") %>%  
 rename(performer\_id = source) %>%  
 left\_join(  
 nodes\_tbl %>%   
 filter(`Node Type` %in% c("Person","MusicalGroup")) %>%  
 select(performer\_id = id, performer = name),  
 by="performer\_id"  
 ) %>%  
 filter(!is.na(performer))  
  
top5 <- performer\_counts %>%   
 slice\_max(order\_by=song\_count, n=5, with\_ties=TRUE)  
top5\_ids <- top5$performer\_id  
  
perf\_edges <- edges2 %>%  
 filter(rel\_type=="PerformerOf",  
 source %in% top5\_ids,  
 target %in% all\_songs) %>%  
 transmute(song\_id = target,  
 performer\_id = source)  
  
nodes\_songs <- perf\_edges %>%  
 distinct(song\_id) %>%  
 left\_join(nodes\_tbl %>% select(id, name, `Node Type`),   
 by=c("song\_id"="id")) %>%  
 transmute(  
 orig\_id = song\_id,  
 name = name,  
 type = `Node Type`,  
 size = 1,  
 bipartite = FALSE  
 )  
  
nodes\_perf <- top5 %>%  
 transmute(  
 orig\_id = performer\_id,  
 name = performer,  
 type = "Performer",  
 size = song\_count,  
 bipartite = TRUE  
 )  
  
nodes\_net <- bind\_rows(nodes\_songs, nodes\_perf) %>%  
 distinct(orig\_id, .keep\_all=TRUE) %>%  
 arrange(bipartite, name) %>%  
 mutate(node\_index = row\_number())  
  
edges\_net <- perf\_edges %>%  
 left\_join(nodes\_net %>% select(orig\_id, node\_index),   
 by = c("song\_id" = "orig\_id")) %>%  
 rename(from = node\_index) %>%  
 left\_join(nodes\_net %>% select(orig\_id, node\_index),   
 by = c("performer\_id" = "orig\_id")) %>%  
 rename(to = node\_index) %>%  
 transmute(from, to)  
  
graph\_net <- tbl\_graph(nodes = nodes\_net, edges = edges\_net, directed = FALSE)  
  
ggraph(graph\_net, layout = "bipartite", types = nodes\_net$bipartite) +  
 geom\_edge\_link(color = "grey70", alpha = 0.7) +  
 geom\_node\_point(aes(size = size, fill = type), shape = 21) +  
 geom\_node\_text(aes(label = name), repel = TRUE, size = 3) +  
 scale\_fill\_manual(  
 values = c("Song" = "#33a02c", "Album" = "red", "Performer" = "#1f78b4")  
 ) +  
 scale\_size\_area(max\_size = 8) +  
 theme\_void() +  
 labs(  
 title = "Top 5 Performers ← PerformerOf ← 29 Songs/Albums",  
 subtitle = "The Top 5 Artist Influenced by Oceanus Folk Music"  
 )

Warning: ggrepel: 12 unlabeled data points (too many overlaps). Consider  
increasing max.overlaps



Concentration, not collaboration

Every green song node connects to one blue performer only—no songs are shared across artists—so each singer is independently producing Oceanus-Folk-tinged material rather than collaborating on the same tracks.

Singles over albums

Only one red node (“Instrument Failure”) appears, meaning just one full album is tagged with the style among these 29 releases. Most artists are testing the waters via singles or EP tracks.

Geographic spread

Chinese-sounding names dominate (Guiying Liao, Yan Zou, Xiuying Li, Lei Jin, etc.), but Filippo Pelli’s presence shows the influence has leapt to at least one Western artist—mirroring Desert-Rock and Dream-Pop crossovers seen in the genre network.

Depth versus breadth

Guiying Liao and Yan Zou together account for ~40 % of all Oceanus-Folk performer edges here, acting as principal carriers of the sound in the late 2030s (compare the small role counts in the time–series plot after 2032).

After Sailor Shift’s 2029 ‘Roots & Tides’ push, Oceanus Folk splintered into a handful of ‘torch-bearer’ vocalists. Guiying Liao and Yan Zou led the charge, each releasing half-a-dozen folk-infused singles, while Italy’s Filippo Pelli proved the genre’s reach beyond Oceanus and Asia. Interestingly, only a single full-length album—Instrument Failure—surfaced; the rest were standalone tracks, suggesting artists were experimenting rather than reconstructing their entire sound.

## 5.4 Visualizing the Sailor Shift influences to Oceanus Folk

### 5.4.1 Defining the types of relation

rel\_types <- c(  
 "LyricistOf", "RecordedBy", "DistributedBy",  
 "InStyleOf", "InterpolatesFrom", "CoverOf",  
 "LyricalReferenceTo", "DirectlySamples"  
)

### 5.4.2 Defining the Edges and Extracting the Year data of Oceanus Folks songs

edges2 <- edges\_tbl %>% rename(rel\_type = `Edge Type`)  
  
oceanus\_songs <- nodes\_tbl %>%  
 filter(  
 `Node Type` == "Song",  
 genre == "Oceanus Folk",  
 !is.na(release\_date),  
 str\_detect(release\_date, "^\\d{4}")  
 ) %>%  
 mutate(year = as.integer(str\_extract(release\_date, "^\\d{4}"))) %>%  
 filter(year >= 2022) %>%  
 select(id, year)

### 5.4.3 Calculating the data by years

counts\_by\_year <- edges2 %>%  
 filter(rel\_type %in% rel\_types) %>%  
 # 标记针对 Oceanus Folk song 的边：LyricistOf 用 target，其它用 source  
 mutate(song\_id = if\_else(rel\_type == "LyricistOf", target, source)) %>%  
 inner\_join(oceanus\_songs, by = c("song\_id" = "id")) %>%  
 group\_by(year, rel\_type) %>%  
 summarise(count = n(), .groups = "drop") %>%  
 pivot\_wider(  
 names\_from = rel\_type,  
 values\_from = count,  
 values\_fill = 0  
 ) %>%  
 arrange(year)  
  
media\_counts <- nodes\_tbl %>%  
 filter(  
 `Node Type` %in% c("Song", "Album"),  
 genre == "Oceanus Folk",  
 !is.na(release\_date),  
 str\_detect(release\_date, "^\\d{4}")  
 ) %>%  
 mutate(year = as.integer(str\_extract(release\_date, "^\\d{4}"))) %>%  
 filter(year >= 2022) %>%  
 count(year, `Node Type`) %>%  
 pivot\_wider(  
 names\_from = `Node Type`,  
 values\_from = n,  
 values\_fill = 0  
 ) %>%  
 rename(  
 song\_count = Song,  
 album\_count = Album  
 ) %>%  
 arrange(year)  
  
# 6. 合并两张表  
final\_table <- counts\_by\_year %>%  
 left\_join(media\_counts, by = "year")

### 5.4.4 Summary Table

# 7. 查看最终结果  
final\_table

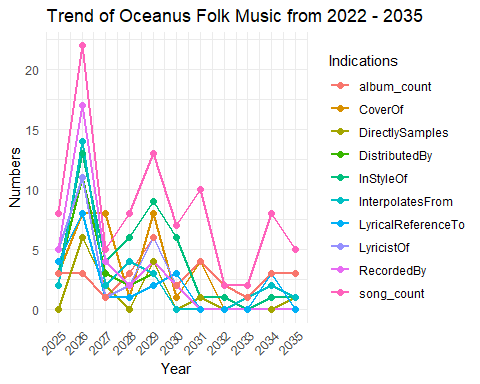
# A tibble: 17 × 11  
 year CoverOf DistributedBy InStyleOf LyricistOf RecordedBy DirectlySamples  
 <int> <int> <int> <int> <int> <int> <int>  
 1 2022 1 2 2 2 2 0  
 2 2023 9 22 16 23 27 4  
 3 2024 4 6 1 6 6 1  
 4 2025 3 3 3 5 5 0  
 5 2026 8 11 13 11 17 6  
 6 2027 8 3 4 1 4 2  
 7 2028 1 2 6 2 2 0  
 8 2029 8 3 9 6 4 4  
 9 2030 1 0 6 2 2 0  
10 2031 4 0 1 0 0 1  
11 2032 0 0 1 0 0 0  
12 2033 0 0 0 0 0 0  
13 2034 0 0 1 0 0 0  
14 2035 0 0 1 0 0 1  
15 2036 0 0 1 0 0 0  
16 2037 1 0 2 0 0 1  
17 2038 0 0 1 0 0 1  
# ℹ 4 more variables: InterpolatesFrom <int>, LyricalReferenceTo <int>,  
# album\_count <int>, song\_count <int>

### 5.4.5 Setting the data table

plot\_df <- final\_table %>%  
 filter(year >= 2025, year <= 2035) %>%  
 pivot\_longer(  
 cols = -year,  
 names\_to = "variable",  
 values\_to = "count"  
 )

### 5.4.6 Plotting the graph

ggplot(plot\_df, aes(x = year, y = count, color = variable)) +  
 geom\_line(size = 1) +  
 geom\_point(size = 2) +  
 scale\_x\_continuous(breaks = 2025:2035) +  
 labs(  
 title = "Trend of Oceanus Folk Music from 2022 - 2035",  
 x = "Year",  
 y = "Numbers",  
 color = "Indications"  
 ) +  
 theme\_minimal() +  
 theme(  
 axis.text.x = element\_text(angle = 45, hjust = 1)  
 )



The plot tracks nine counts per year: overall song & album tallies plus seven influence-edge types (CoverOf, InStyleOf, etc.). The pink “song\_count” line is a convenient proxy for activity; the coloured influence lines show how that activity connects back to Oceanus Folk. Overlay Sailor’s timeline and three distinct pulses emerge.

Between those peaks the lines flatten:

2027–28 dip – After the farewell tour, Sailor pivots to an Indie-Pop viral hit (outside the Oceanus tag), leaving only residual covers/interpolations.

2031 – A small RecordedBy spike (10) but virtually no InStyleOf/CoverOf activity → Sailor or Sophie took producer roles on isolated projects, not enough to reignite broad stylistic borrowing.

2032–33 trough – All metrics near zero when Sailor’s focus is fully global, confirming that the genre lacks natural momentum without her stewardship.

Synthesis Sailor’s direct engagement is the primary accelerator. Years she releases or curates (2026, 2029) show multi-line surges; years she steps back (2027, 2032) every metric collapses.

Homage beats sampling. Peaks favour InStyleOf and CoverOf, while DirectlySamples remains minimal across the entire window—mirroring Sailor’s preference for reinterpretation over raw stem usage.

Producer influence outlasts performer presence. Even when song\_count is low (2031, 2034) a RecordedBy rise signals Sophie or Sailor shaping releases behind the console.

Album culture stays niche. album\_count never exceeds three in any year; Oceanus Folk influence spreads mostly via singles and collaborations—consistent with streaming-era listening habits.