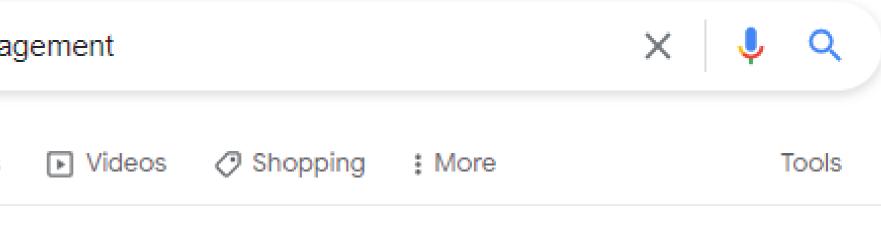
Risk Reporting and Risk Monitoring during the Zombie Apocalypse Benoit Ladouceur Director, Bureau of Institutional Research



UQÀM	Google	risk-based performance managed
Université du Québec à Montréal		🔍 All 🔝 Images 🗉 News
		About 1,100,000,000 results (0.71

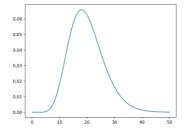


1 seconds)

Presentation structure

You are the Zombie!		WALKING DEAD Originalization	WORLD WAR AN ORAL HISTORY OF THE ZOMBIE WAR MAX BROOKS
Heat maps	 Easy, conceptual and no fancy tricks 	 There may be some statistical concepts 	 Some coding and statistics may be involved
Medium Risk of dying due to famine	We can sustain 5 to 45 colonists	We have 90% chance of sustaining between 10 and 35 colonists	Updated with today's data, we have a 90% chance of sustaining between 12 and 37, with potable water being the key factor
		0.06 - 0.05 -	Prediction error Posterior Likelihood







Uncertainty

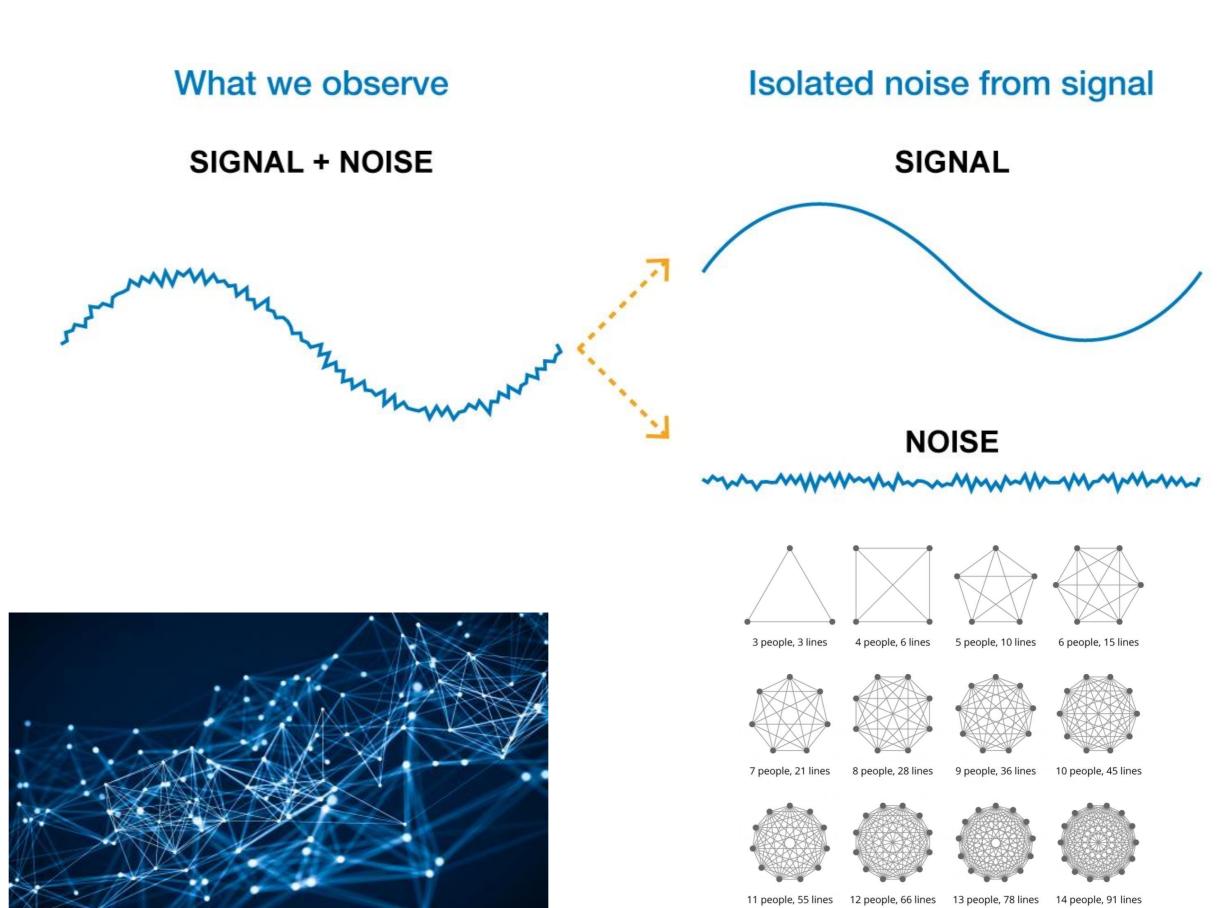
2

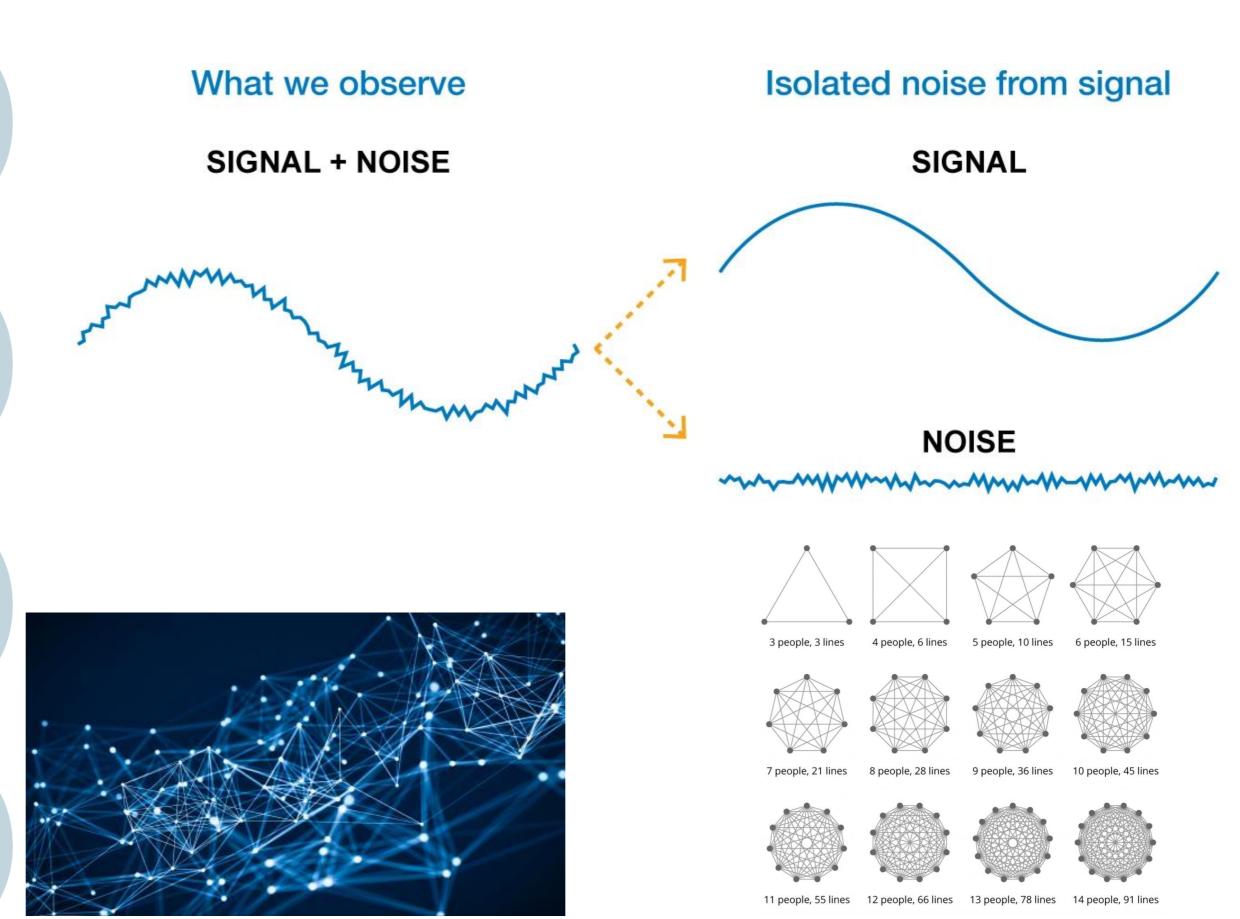
Signal and Noise



•Sometime, simple methods may work.

•But complexity is a...





Preparedness





Robust

Resilient





Warned

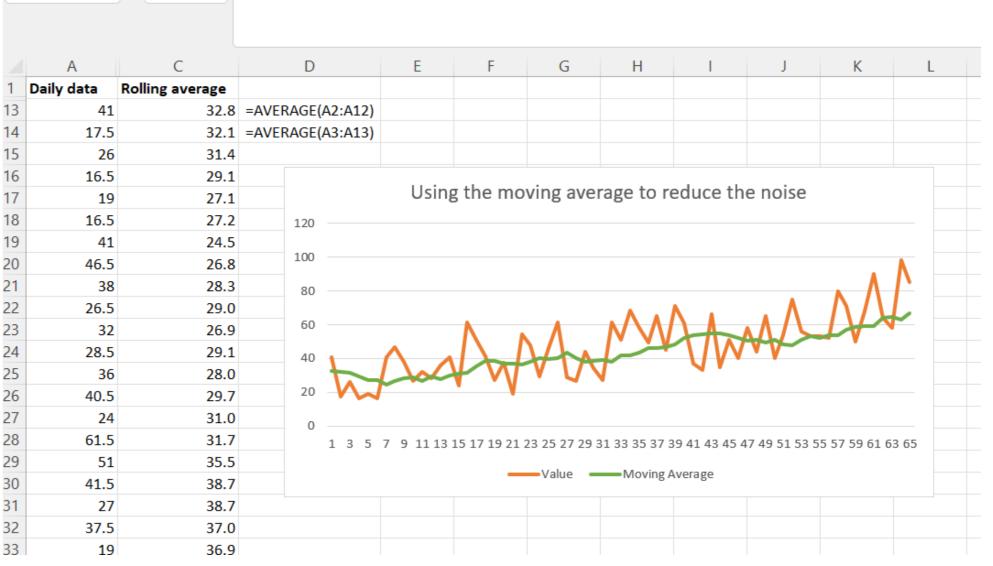




- Cut the jargon and take the time to explain principles.
- Talking in ranges and presenting assumptions.

Talking about risks and trends







 $\bar{a}_{\rm SM} = \bar{a}$

C14

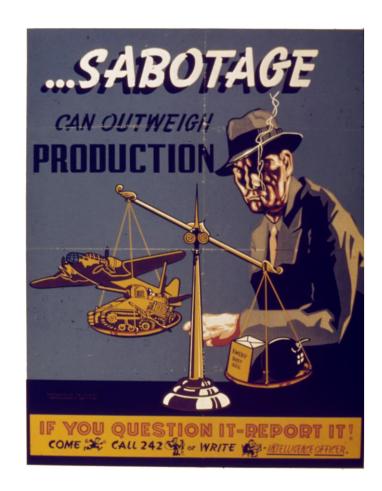


$= \bar{a}_{\text{SM_prev}} + \frac{1}{n}(x_M - x_{M-n})$

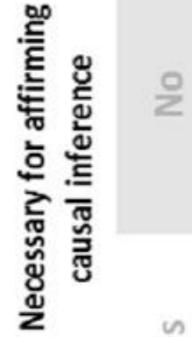
\checkmark : $\times \checkmark f_x$ =AVERAGE(A3:A13)

Causality

Some qualitative ulletmethods are useful, even when trying to establish causality.

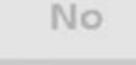






Yes





1. Straw-in-the-

a. Passing: Affirm relevand hypothesis, but does not a b. Failing: Hypothesis is no but is slightly weakened.

2. Hoop

a. Passing: Affirm relevand hypothesis, but does not c b. Failing: Eliminates hypo

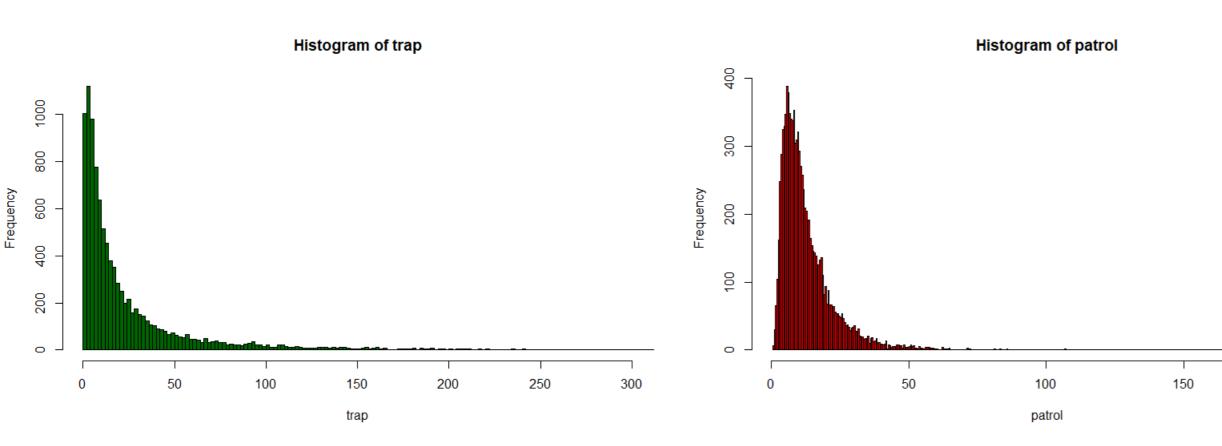
Lintelo, D. & Munslow, T. & Pittore, Katherine & Lakshman, Rajith. (2019).



Sufficient for affirming causal inference

	Yes
Wind	3. Smoking-Gun
ce of confirm it. ot eliminated,	 a. Passing: Confirm hypothesis. b. Failing: Hypothesis is not eliminated, but is somewhat weakened.
ce of confirm it. othesis.	 4. Double Decisive a. Passing: Confirm hypothesis and eliminates others. b. Failing: Eliminates hypothesis.

Objectives level using R

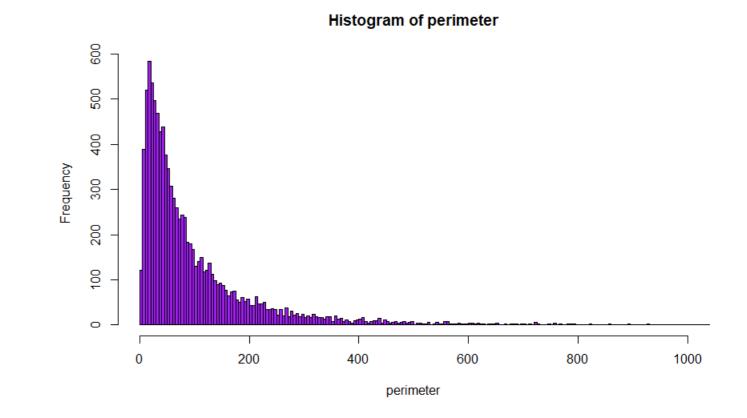


trap <- rlnorm(10000, log(12), log(4))
patrol <- rlnorm(10000, log(10), log(2))
perimeter <- rlnorm(10000, log(60), log(3))</pre>

p1 <- hist(trap, breaks=1000, xlim=c(1,300), col ="darkgreen")
p2 <- hist(patrol, breaks=500, xlim=c(1,200), col ="red")
p3 <- hist(perimeter, breaks=1000, xlim=c(1,1000), col ="purple")</pre>







#RAW2022|7

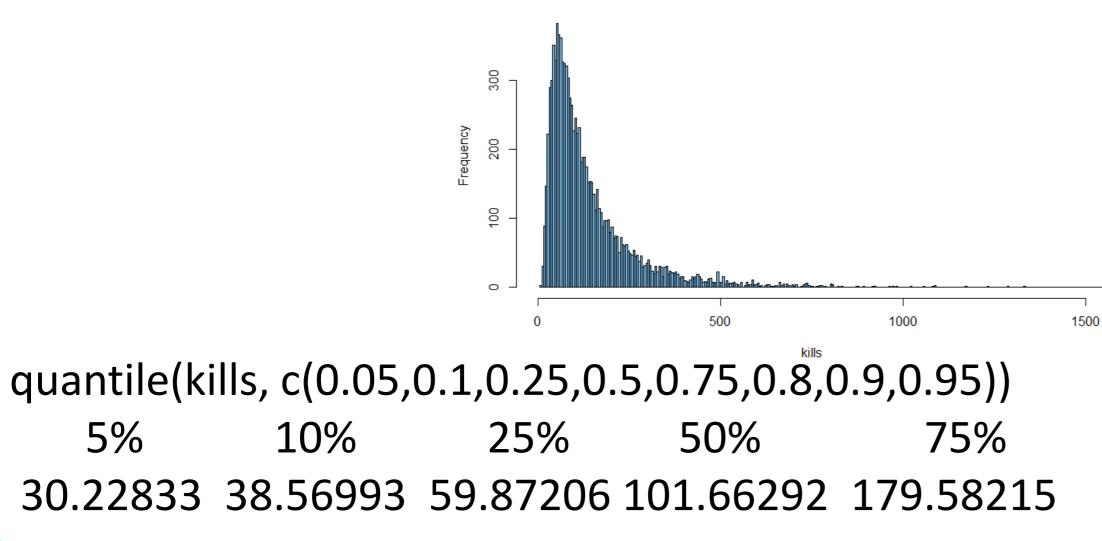
200

Objectives level using R



kills <- trap + patrol + perimeter hist(kills, breaks=1000, xlim=c(1,1500), col ="skyblue2")

Histogram of kills



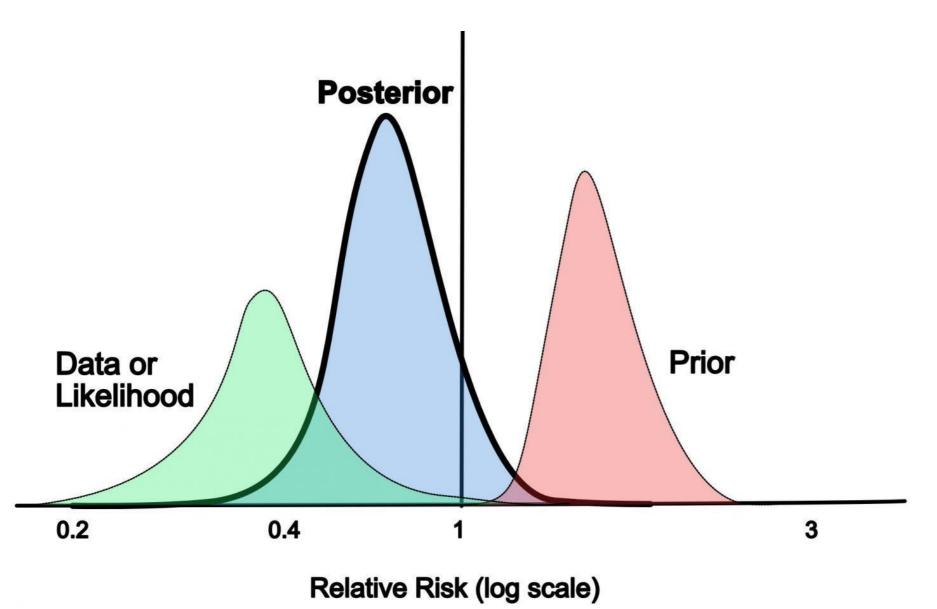




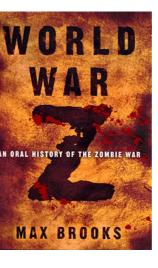
80% 90% 95% 427.18523 207.69101 303.91936

Bayesian updating

• Updating you beliefs based on new information.

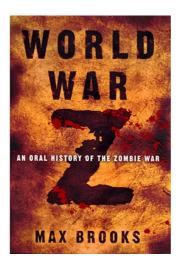












 Seasonal and Trend decomposition using Loess

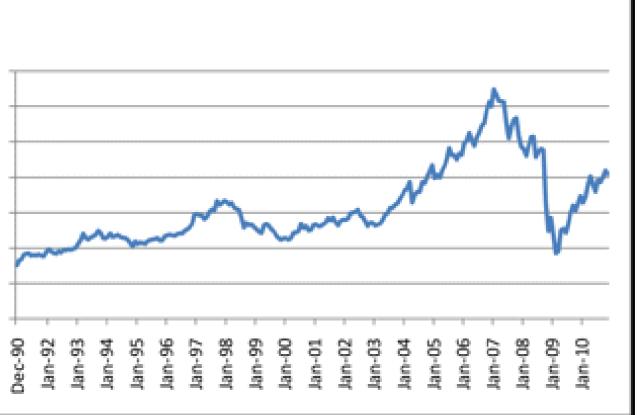
• ARIMA



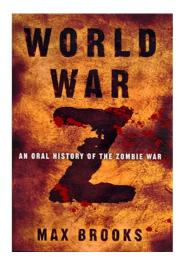


700.00 600.00 500.00 400.00 300.00 200.00 100.00 0.00





Model validation



I am the Chosen One, my models don't need validation





You are kidding, right?





Thanks for attending, and make sure to avoid the zombification of your **Board!**

Picture courtesy of brgfx







- # Risk Awareness Week 2022 Risk Reporting and Risk Monitoring during the Zombie Apocalypse – R Code
- # Is my assumption (belief) standing the test of time? •
- library(bayesrules) #loading packages ullet
- library(tidyverse) ullet
- library(rstan) ullet
- library(bayesplot) ullet
- library(broom.mixed) ullet
- library(janitor)
- library(fpp3) \bullet



- # Small Monte Carlo simulation to assess number of zombie kills as part of colony performance review
- trap <- rlnorm(10000, $\log(12)$, $\log(4)$)
- patrol <- rlnorm(10000, log(10), log(2))
- perimeter <- rlnorm(10000, log(60), log(3)) \bullet
- kills <- trap + patrol + perimeter
- p1 <- hist(trap, breaks=1000, xlim=c(1,300), col ="darkgreen")
- p2 <- hist(patrol, breaks=500, xlim=c(1,200), col ="red")
- p3 <-hist(perimeter, breaks=1000, xlim=c(1,1000), col ="purple")
- hist(kills, breaks=1000, xlim=c(1,1500), col ="skyblue2")





- quantile(kills, c(0.05,0.1,0.25,0.5,0.75,0.8,0.9,0.95))
- #
- #Bayesian updating
- p = seq(0,1, length=100)
- #Fast vs Slow Zombies
- plot(p, dbeta(p, 3, 8), type='l') #relatively weak prior
- qbeta(c(0.05,0.95), 3,8)
- plot(p, dbeta(p, 28, 96), type='l')
- qbeta(c(0.05,0.95), 28,96)
- plot_beta_binomial(alpha=3,beta=8, y=28,n=124)



- prior <- pbeta(0.25,3,8)
- prior
- posterior <- pbeta(0.25, 28,96)
- posterior
- posterior/ (1-posterior) #odds



- #Gamma-Poisson Conjugacy using the bayesrule library
- #From a sample calculating the lambda.
- #Trial and errors using Gamma distribution to figure out the lambda from my Poisson
- #I think I have an average 6 zombies per hour, with some zombies every hour and very rarely 12 or more
- plot_gamma(shape=8, rate=3)
- plot_gamma(shape=8, rate=2)
- plot_gamma(shape=8.5, rate=2)
- plot_gamma(shape=9, rate=2)



the lambda from my Poisson e zombies every hour and very rarely

Code

- plot_gamma(shape=10, rate=2)
- plot_gamma(shape=10, rate=3)
- plot_gamma(shape=12, rate=2)#Decent prior for about 3 to 10 with an average of 6 ullet
- summarize_gamma(12,2)
- plot_poisson_likelihood(y=c(3,4,12,2,5,6,7,14,3,6,8), lambda_upper_bound = 50)
- #With new data
- plot gamma poisson(shape=12,rate=2,sum y=70, n=11) ullet
- summarize_gamma_poisson(shape=12,rate=2,sum_y=70, n=11)



Code

- #STL and ARIMA
- us_finance_employment <- us_employment %>% filter(year(Month) >= 1970,
- Title== "Financial Activities") %>% select(-Series_ID)
- autoplot(us_finance_employment)
- model <- us_finance_employment %>% model(stl = STL(Employed))
- components(model)
- components(model) %>% autoplot()
- model1 <- us_finance_employment %>% model(ARIMA(Employed, stepwise = FALSE, approx = FALSE))
- forecast(model1, h=48) %>% autoplot(us_finance_employment)

