Project 1

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QUESTION:

It is known that masking is effective at preventing the transmission of disease, however, there are many factors that also in tandem influence the effectiveness of masks. In this design based question we seek to find out how effective masks need to be to decrease the infected population by 50% while also accounting for external factors like mask compliance, etc.

This question is particularly important as in the last few years the prevalence and importance of masks has skyrocketed, namely with the COVID-19 pandemic. This question can help better illustrate the importance of mask efficacy but also how it relates to other factors like compliance.

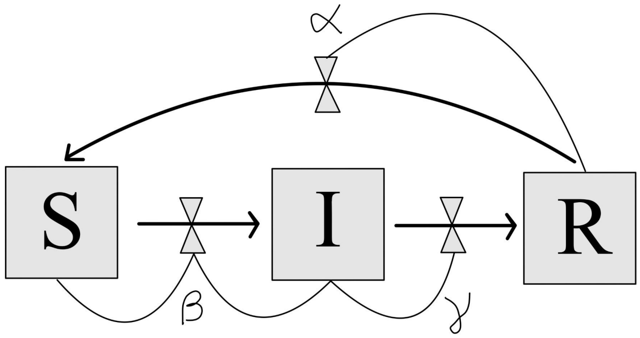
Theme	Unmasking the mask studies: why the effectiveness of surgical masks in preventing respiratory infections has been underestimated By Pratyush K Kollepara, Alexander F Siegenfeld, Nassim Nicholas Taleb,	An evidence review of face masks against COVID-19 By Jeremy Howard, Anne W. Rimoin, , Austin Huang, Zhiyuan Li
Theme: Adherence to Masking protocol is very important	Studies have shown that full adherence to masking protocol even with underpowered surgical masks can greatly stop disease transmission.	Public mask wearing is most effective at reducing spread of the virus when compliance is high. The least ineffective mask (cloth masks) are even recommended during shortages as compliance is very important.
Theme: Blue surgical masks are usually very ineffective.	Surgical masks have little to no effect on the chance of infection.	Estimate mean decreases in infection risk between 4% and 15% for surgical masks.

METHODOLOGY:

DESCRIPTION

The model(s) shown in this project show two things. First, how the effectiveness of masks directly influences the infected population in our SIR model. Second, which illustrates how the compliance rate also influences the infected population.

Shown below is a stock and flow diagram of our SIR model which is modified to include a flow from recovered back to susceptible.



In this stock and flow diagram we can see it is just a slightly modified SIR stock and flow diagram.

S is the susceptible stock.

I is the infected stock.

R is the recovered stock.

The flow from S to I represents people being infected and this flow rate is influenced by beta.

The flow from I to R represents infected people recovering and this flow rate is influenced by gamma.

The flow from R to S represents people becoming resuspectable and this flow rate is influenced by alpha.

For the most part we are sticking to the standard SIR update equations. However, the main changes with our SIR update equations lie solely with the beta value which determines our infectivity rate. In our definition of our beta value that goes into our SIR simulation we keep the base infectivity rate; however, we also account for things like compliance (c) which can either keep our base infectivity or decrease it. We also have the effectiveness of masks (e) which can also keep our base infectivity or decrease it.

There are several assumptions that our SIR model does make which does affect its overall accuracy. These assumptions are no one dies in our model, age doesn't affect the infectivity rate, and that there are no other preventative measures other than masking. These assumptions are acceptable in relation to our model as without these assumptions our model would greatly increase in complexity. Furthermore, deaths would create another flow out of the model and since we are strictly focusing on the infected population, we don't need to overcomplicate finding the 50% point.

```
% Initializing update equations

%   s = current number of susceptible individuals
%   i = current number of infected individuals
%   r = current number of recovered individuals

%   beta = infection rate parameter
%   gamma = recovery rate paramter
%   alpha = resuspetibility rate parameter
```

```
%   s_n = next number of susceptible individuals
%   i_n = next number of infected individuals
%   r_n = next number of recovered individuals

% Update equations

% compute new infections and recoveries
% infected = beta * i * s
% recovered = gamma * i
% resusceptible = alpha * r;

% s_n = s - infected + resusceptible;
% i_n = i + infected - recovered;
% r_n = r + recovered - resusceptible;
```

DEVELOPMENT

For most of our initialization parameters we used the standard S = 99 I = 1 and R = 0. For our other variables such as beta and gamma we really determined these values from other worksheets. The only values we did set were alpha and e and c. For determining how effective masks needed to be we had a set compliance value of 60 percent. We did a parameter sweep over every value of E to determine what value E needed to be in order for the infected population to be cut down by 50 percent.

In order to ensure verification within our model we established some assert statements. In our model we had to makes sure the total population remained constant as there were no flows out of the due to factors like death, etc.

```
%all(abs(S + I + R - 100) < 1e-3)
%all(abs(s + i + r - 100) < 1e-3)
%all(abs(Ipeak_all_e(idx_e) - max(I(1,:))/2) < 1e-3)
```

RESULTS:

METRICS AND SWEEPS

To answer the question of how effective masks need to be in order to cut the infectious population by 50% we did a parameter sweep on the efficiency of masks (e) and the compliance rate. These variables are chosen as they directly influence the base infection rate as they can dampen its strength.

```
%Definining initial state
% A population of 100 persons, 99 susceptible and 1 infectious
s_1 = 99;
i_1 = 1;
r_1 = 0;

%Base infection rate (Determined via previous worksheets)
betaI = 0.05;
```

```
%Base recovery rate based on data (1/Weeks)
gamma = 0.5;

%Resuseptibility rate (Assumption that immunity lasts for 6 months)
alpha = 1/24;

%Different mask effectiveness
e=[0, 0.94, 0.8, 0.5, 0.1];

%Arbitrary mask compliance rate
c=0.6;
```

As shown below the results of the parameter sweeps of the first graph comparing the efficacy of masks to the infected peak (with a population compliance of 60%) showed that in that scenario masks only need to have a 42.14% efficacy rate to cut the base infected peak by 50%.

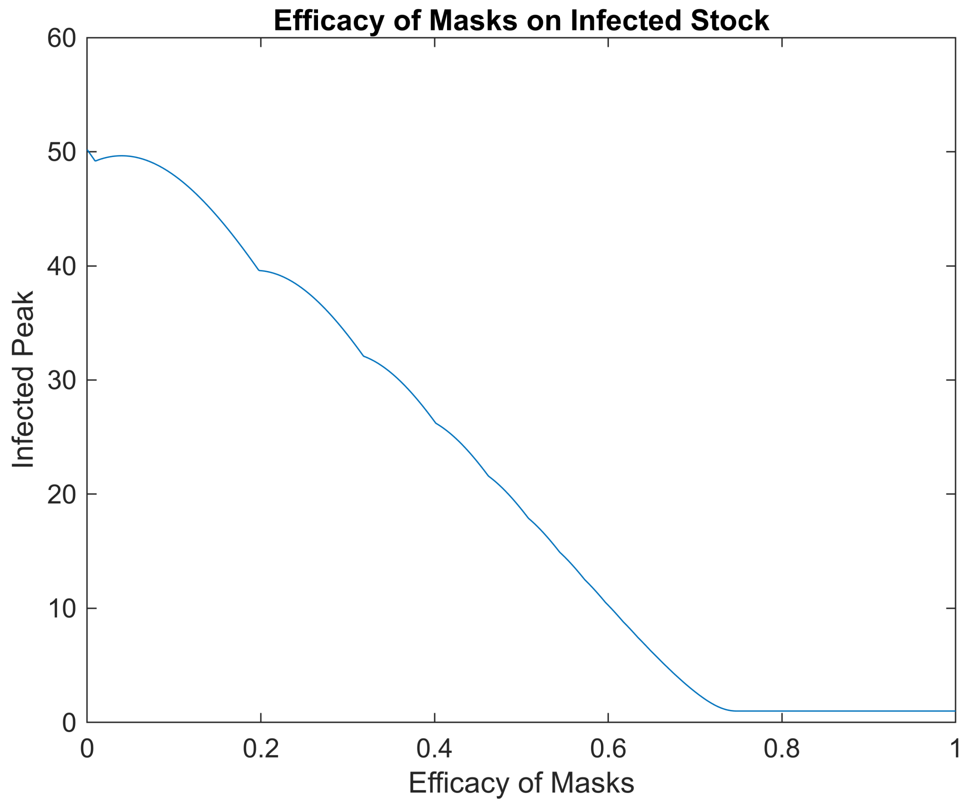
```
%Initialize data for peak infection w/o masks
for i=1:5
    beta(i)=betaI*(1-e(i))*(1-c);
    [S(i,:), I(i,:), R(i,:), W] = project1_simulate_sir(s_1, i_1, r_1, beta(i),
gamma, alpha, 100);
end

name=["No Mask", "KF94", "KF80", "KF50", "Blue Mask"];
```

```
%Parameter Sweep over Effectiveness of Masks and their effect on Infected Peak
(Compliance rate of 60%)
e_all = linspace(0, 1, 1000);
beta_all_e = betaI*(1-e_all)*(1-c);

for j = 1:length(e_all)
    [s, i, r, w] = project1_simulate_sir(s_1, i_1, r_1, beta_all_e(j), gamma,
alpha, 100);
    Ipeak_all_e(j)=max(i);
end

%Plot
figure()
plot(e_all, Ipeak_all_e)
xlabel("Efficacy of Masks")
ylabel("Infected Peak")
title("Efficacy of Masks on Infected Stock")
```




```
%Determines at what E value in which infected persons are cut down by 50%
peak_number_of_infected_persons_without_mask = max(I(1,:))
```

```
peak_number_of_infected_persons_without_mask = 50.1849
```

```
fiftypercent_peak = max(I(1,:))/2
```

```
fiftypercent_peak = 25.0924
```

```
temp_e = abs(max(I(1,:))/2 - Ipeak_all_e);
idx_e = find(temp_e == min(abs(max(I(1,:))/2 - Ipeak_all_e)));
approximate_fiftypercent_peak = Ipeak_all_e(idx_e)
```

```
approximate_fiftypercent_peak = 25.0934
```

```
approximate_e_for_fiftypercent_peak = e_all(idx_e)
```

```
approximate_e_for_fiftypercent_peak = 0.4214
```

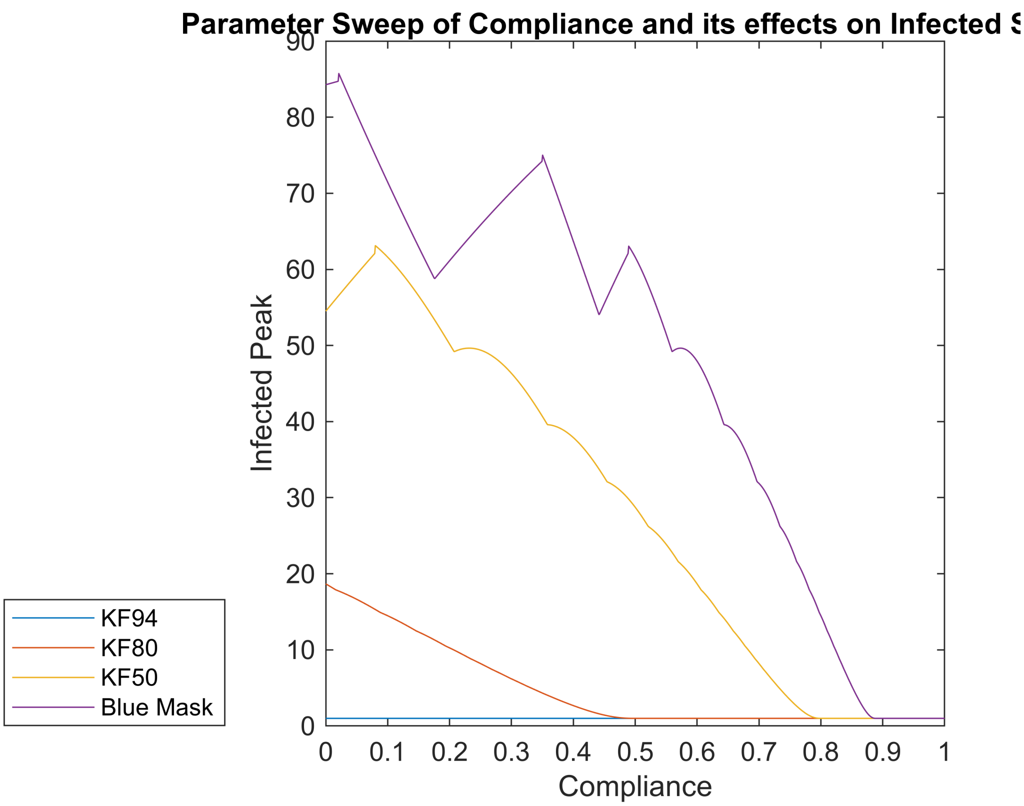
The second parameter sweep illustrates the relationship between compliance and the infected peak. In the graph it shows that no matter how low the mask efficancy is as long as the compliance rate reaches 100% the infected peak would be only 1.

```
c_all = linspace(0, 1, 1000);
for j = 1:5
    for k = 1:1000
        beta_all_c(j, k) = betaI*(1-e(j))*(1-c_all(k));
```

```
    end
end
%beta_all_c = betaI*(1-e_middle)*(1-c_all);

for j = 1:5
    for k = 1:length(e_all)
        [s, i, r, w] = project1_simulate_sir(s_1, i_1, r_1, beta_all_c(j, k),
gamma, alpha, 52);
        Ipeak_all_c(j, k)=max(i);
    end
end

figure()
for j = 2:5
    plot(c_all, Ipeak_all_c(j, :), 'DisplayName', name(j)); hold on
end
xlabel("Compliance")
xticks(0: (1/10):1);
ylabel("Infected Peak")
title("Parameter Sweep of Compliance and its effects on Infected Stock")
legend('Location', 'southwestoutside')
```




```
peak_number_of_infected_persons_without_mask = max(I(1,:))
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```
peak_number_of_infected_persons_without_mask = 50.1849
```

```
fiftypercent_peak = max(I(1,:))/2
```

```
fiftypercent_peak = 25.0924
```

```


all(abs(S + I + R - 100) < 1e-3)
```

```
ans = 1×100 logical array
   1   1   1   1   1   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0⋯
```

```
all(abs(s + i + r - 100) < 1e-3)
```

```
ans = logical
   1
```

```
all(abs(Ipeak_all_e(idx_e) - max(I(1,:))/2) < 1e-3)
```

```
ans = logical
   1
```

ANALYSIS

The data and parameter sweep over E and C illustrate two important trends. One is how infection peaks lows as the efficacy of masks increases, and two which is how as compliance increases infection peak also decreases for all efficacy values. Therefore, our results add another layer of complexity to answering this question as we have two ways to technically answer this question.

INTERPRETATION:

THEREFORE

From our results we can really come up with two solutions to our modelling question. One is that assuming compliance is at 60% then the efficacy of masks only needs to be 42.14% to cut the infected peak by 50%. The second solution is more theoretical as for instance we can use the least effective mask (which in our case is the blue mask) and if the compliance is 80% then the infected population is cut down by 50%.

LIMITATIONS AND FUTURE WORK

Due to the nature of our model, there are several limitations to our overall real-world validation and accuracy. One of which is our initial assumptions of our model. Obviously in the real world there are other factors like age, death, gender, etc. which affect our model, and this prevents us from achieving full validation. Additionally, the basis of our SIR model is flawed as our update equations aren't derivative based. Our current SIR model uses the time basis of weeks which prevents us from gathering more data which a derivative based SIR model can gather. With that limitation, MATLAB must make assumptions about our model, thus further reducing accuracy.

In the future if more work was to be done on this model, we would start addressing basic inaccuracies by considering age, gender, etc. Furthermore, we could implement the full SIR model to increase accuracy, so MATLAB doesn't have to make assumptions. Other solutions could just be using a completely better model that better matches our data.