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# 3D Data Processing **Ceres-Solver Tutorial**

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# Goal

Solve robustified **non-linear least squares** problems of the form

The diagram illustrates the components of the optimization problem. The equation is 
$$\min_{\mathbf{x}} \quad \frac{1}{2} \sum_i \rho_i \left( \|f_i(x_{i_1}, \dots, x_{i_k})\|^2 \right)$$
 Annotations: A red oval encircles the entire sum term, labeled "Residual Block". A blue oval encircles the inner function  $f_i(x_{i_1}, \dots, x_{i_k})$ , labeled "Parameter Block/s". A blue line points from the text "Loss Function (Huber, Cauchy ...)" to the  $\rho_i$  term. A blue line points from the text "Cost Function" to the squared norm  $\| \cdot \|^2$ .

$$\min_{\mathbf{x}} \quad \frac{1}{2} \sum_i \rho_i \left( \|f_i(x_{i_1}, \dots, x_{i_k})\|^2 \right)$$

Residual Block

Loss Function (Huber, Cauchy ...)

Cost Function

Parameter Block/s

# Example

Find the minimum of the function

$$\frac{1}{2}(10 - x)^2$$

Solve it with Ceres:

- 1) Write a functor that will evaluate the residual
- 2) Build the non-linear least squares problem
- 3) Setup and run the solver

```
struct CostFunction {  
    template <typename T>  
    bool operator()(const T* const x, T* residual) const {  
        residual[0] = 10.0 - x[0];  
        return true;  
    }  
};
```

```
int main(int argc, char** argv) {  
    google::InitGoogleLogging(argv[0]);  
  
    // The variable to solve for with its initial value.  
    double initial_x = 5.0;  
    double x = initial_x;  
  
    // Build the problem.  
    Problem problem;  
  
    // Set up the only cost function (also known as residual). This uses  
    // auto-differentiation to obtain the derivative (jacobian).  
    CostFunction* cost_function =  
        new AutoDiffCostFunction<CostFunction, 1, 1>(new CostFunction);  
    problem.AddResidualBlock(cost_function, nullptr, &x);  
  
    // Run the solver!  
    Solver::Options options;  
    options.linear_solver_type = ceres::DENSE_QR;  
    options.minimizer_progress_to_stdout = true;  
    Solver::Summary summary;  
    Solve(options, &problem, &summary);  
  
    std::cout << summary.BriefReport() << "\n";  
    std::cout << "x : " << initial_x  
        << " -> " << x << "\n";  
  
    return 0;  
}
```

# Example

Find the minimum of the function

$$\frac{1}{2}(10 - x)^2$$

## OUTPUT

iter	cost	cost_change	gradient	step	tr_ratio	tr_radius	ls_iter	iter_time	total_time
0	4.512500e+01	0.00e+00	9.50e+00	0.00e+00	0.00e+00	1.00e+04	0	5.33e-04	3.46e-03
1	4.511598e-07	4.51e+01	9.50e-04	9.50e+00	1.00e+00	3.00e+04	1	5.00e-04	4.05e-03
2	5.012552e-16	4.51e-07	3.17e-08	9.50e-04	1.00e+00	9.00e+04	1	1.60e-05	4.09e-03

Ceres Solver Report: Iterations: 2, Initial cost: 4.512500e+01, Final cost: 5.012552e-16, Termination: CONVERGENCE  
x : 5.0 -> 10

# Automatic differentiation

- Ceres can compute automatically the derivatives wrt the parameters vector while computing residuals
- The parameters can be divided into "blocks", as for example done in bundle adjustment ("camera" blocks and "point" blocks), for simplify managing the sparsity

# Adding residuals

For each residual, we need to add a corresponding "residual block" to the optimization problem:

```
ceres::Problem problem;
for( /* iterate for each data point */ )
{
    ceres::CostFunction* cost_function = ...;

    problem.AddResidualBlock( cost_function,
                             param_block1, param_block2, ...);
}
```

# Adding residuals

We need to define a functor (just a class or struct which defines the operator() ) that computes the residual:

```
struct Functor
{
    template <typename T> bool operator()(const T* const param_block1,
                                         const T* const param_block2,
                                         ...,
                                         T* residuals) const
    {
        // Compute the residuals given the input parameters blocks
        return true; // Success
    }
}
```

# Adding residuals

Then we use this functor to construct the const function:

```
Functor funct = new Functor(...);  
ceres::CostFunction* cost_function = new  
ceres::AutoDiffCostFunction<Functor, Nr, Nb1, Nb2, ... >(funct);
```

N<sub>r</sub>: dimension of a single residual

N<sub>b1</sub>: dimension of parameters block 1

N<sub>b2</sub>: dimension of parameters block 2

....

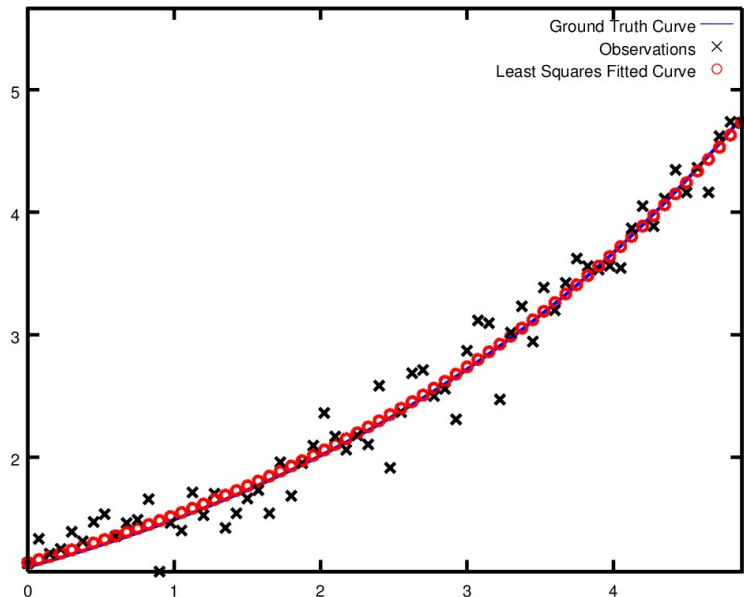


# Curve Fitting

Given a set of observed data points, find the best fitting exponential curve

$$y = e^{mx+c}$$

```
struct ExponentialResidual {  
    ExponentialResidual(double x, double y)  
        : x_(x), y_(y) {}  
  
    template <typename T>  
    bool operator()(const T* const m, const T* const c, T* residual) const {  
        residual[0] = y_ - exp(m[0] * x_ + c[0]);  
        return true;  
    }  
  
private:  
    // Observations for a sample.  
    const double x_;  
    const double y_;  
};
```

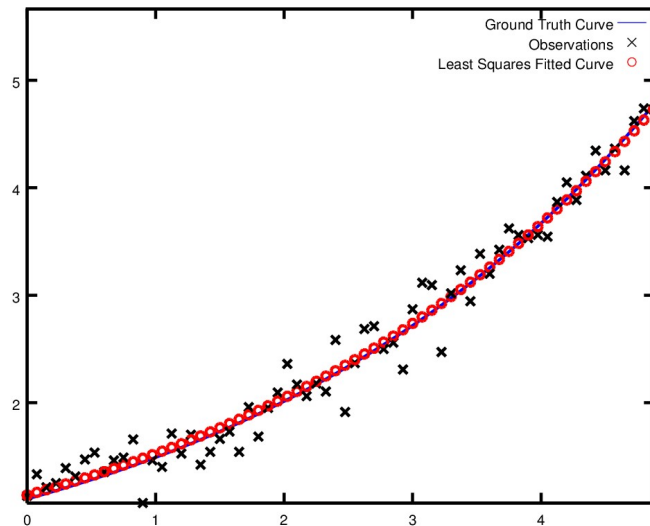


```
double m = 0.0;  
double c = 0.0;  
  
Problem problem;  
for (int i = 0; i < kNumObservations; ++i) {  
    CostFunction* cost_function =  
        new AutoDiffCostFunction<ExponentialResidual, 1, 1, 1>(  
            new ExponentialResidual(data[2 * i], data[2 * i + 1]));  
    problem.AddResidualBlock(cost_function, nullptr, &m, &c);  
}
```

# Curve Fitting

Given a set of observed data points, find the best fitting exponential curve

$$y = e^{mx+c}$$



iter	cost	cost_change	gradient	step	tr_ratio	tr_radius	ls_iter	iter_time	total_time
0	1.211734e+02	0.00e+00	3.61e+02	0.00e+00	0.00e+00	1.00e+04	0	5.34e-04	2.56e-03
1	1.211734e+02	-2.21e+03	0.00e+00	7.52e-01	-1.87e+01	5.00e+03	1	4.29e-05	3.25e-03
2	1.211734e+02	-2.21e+03	0.00e+00	7.51e-01	-1.86e+01	1.25e+03	1	1.10e-05	3.28e-03
3	1.211734e+02	-2.19e+03	0.00e+00	7.48e-01	-1.85e+01	1.56e+02	1	1.41e-05	3.31e-03
4	1.211734e+02	-2.02e+03	0.00e+00	7.22e-01	-1.70e+01	9.77e+00	1	1.00e-05	3.34e-03
5	1.211734e+02	-7.34e+02	0.00e+00	5.78e-01	-6.32e+00	3.05e-01	1	1.00e-05	3.36e-03
6	3.306595e+01	8.81e+01	4.10e+02	3.18e-01	1.37e+00	9.16e-01	1	2.79e-05	3.41e-03
7	6.426770e+00	2.66e+01	1.81e+02	1.29e-01	1.10e+00	2.75e+00	1	2.10e-05	3.45e-03
8	3.344546e+00	3.08e+00	5.51e+01	3.05e-02	1.03e+00	8.24e+00	1	2.10e-05	3.48e-03
9	1.987485e+00	1.36e+00	2.33e+01	8.87e-02	9.94e-01	2.47e+01	1	2.10e-05	3.52e-03
10	1.211585e+00	7.76e-01	8.22e+00	1.05e-01	9.89e-01	7.42e+01	1	2.10e-05	3.56e-03
11	1.063265e+00	1.48e-01	1.44e+00	6.06e-02	9.97e-01	2.22e+02	1	2.60e-05	3.61e-03
12	1.056795e+00	6.47e-03	1.18e-01	1.47e-02	1.00e+00	6.67e+02	1	2.10e-05	3.64e-03
13	1.056751e+00	4.39e-05	3.79e-03	1.28e-03	1.00e+00	2.00e+03	1	2.10e-05	3.68e-03

Ceres Solver Report: Iterations: 13, Initial cost: 1.211734e+02, Final cost: 1.056751e+00, Termination: CONVERGENCE

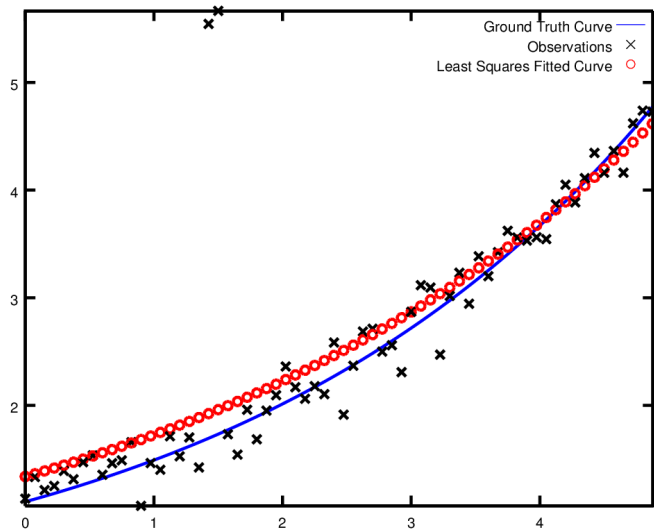
Initial m: 0 c: 0

Final m: 0.291861 c: 0.131439

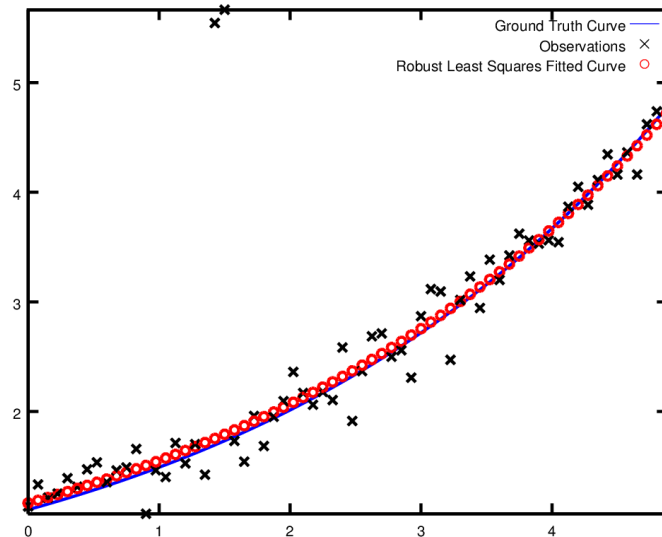
# Robust Curve Fitting

$$y = e^{mx+c}$$

Without Loss Function



With Loss Function



Exploit loss functions for reducing the influence of outliers

```
problem.AddResidualBlock(cost_function, new CauchyLoss(0.5) , &m, &c);
```

# References

- [http://ceres-solver.org/nns\\_tutorial.html](http://ceres-solver.org/nns_tutorial.html)
- [http://ceres-solver.org/nns\\_tutorial.html#bundle-adjustment](http://ceres-solver.org/nns_tutorial.html#bundle-adjustment)