Iterated Vector Fields and Conservatism, with Applications to Federated Learning

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Abstract

We study when iterated vector fields (vector fields composed with themselves) are conservative. We give explicit examples of vector fields for which this self-composition preserves conservatism. Notably, this includes gradient vector fields of loss functions associated to some generalized linear models (including non-convex functions). As we show, characterizing the set of smooth vector fields satisfying this condition yields non-trivial geometric questions. In the context of federated learning, we show that when clients have loss functions whose gradient satisfies this condition, federated averaging is equivalent to gradient descent on a surrogate loss function. We leverage this to derive novel convergence results for federated learning. By contrast, we demonstrate that when the client losses violate this property, federated averaging can yield behavior which is fundamentally distinct from centralized optimization. Finally, we discuss theoretical and practical questions our analytical framework raises for federated learning.

1 Introduction

In this work, we consider vector fields of the form $V : \mathbb{R}^n \to \mathbb{R}^n$. Recall that V is conservative if there is some function $f : \mathbb{R}^n \to \mathbb{R}$ such that $V = \nabla f$. We are interested in whether *iterated* vector fields (vector fields of the form $V \circ V \circ \cdots \circ V$) are conservative. This question has rich connections to a variety of areas, including differential geometry, dynamical systems, and optimization. As we will show, conservative iterated vector fields are particularly important for understanding optimization algorithms for federated learning.

Notation. Let $\mathcal{V}(\mathbb{R}^n, \mathbb{R}^m)$ denote the collection of functions from $\mathbb{R}^n$ to $\mathbb{R}^m$. We let $\mathcal{D}(\mathbb{R}^n, \mathbb{R}^m)$ denote the subset of differentiable functions, and $\mathcal{C}^k(\mathbb{R}^n, \mathbb{R}^m)$ denote the subset of $\mathcal{C}^k$ functions. If $m = n$, we abbreviate these by $\mathcal{V}(\mathbb{R}^n)$, $\mathcal{D}(\mathbb{R}^n)$ and $\mathcal{C}^k(\mathbb{R}^n)$. Throughout, $\|\cdot\|$ denotes the ℓ_2 norm on $\mathbb{R}^n$ with corresponding inner product $\langle \cdot, \cdot \rangle$. We let $I \in \mathcal{V}(\mathbb{R}^n)$ denote the identity map.

Given $V \in \mathcal{V}(\mathbb{R}^n)$, we use exponents to denote repeated iterations of V. That is, for $k \geq 1$ we define:

$$V^k(x) := \underbrace{V \circ V \circ \cdots \circ V}_{\text{k times}}(x)$$

By convention, for any $V \in \mathcal{V}(\mathbb{R}^n)$ we define $V^0 := I$.

Summary. Let $V \in \mathcal{V}(\mathbb{R}^n)$, and let k be a positive integer. We study the following question.

Question 1. *If V is conservative, is V^k also conservative?*

This leads to the following definition.

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Definition 1. *V is k-conservative if V^k is conservative. V is ∞-conservative if V^k is conservative for all $k \geq 1$.*

For convenience, we use "conservative" and "1-conservative" interchangeably. In a slight abuse of notation, we say that $\mathcal{A} \subseteq \mathcal{V}(\mathbb{R}^n)$ is k-conservative if for all $V \in \mathcal{A}$, V is k-conservative. In order to show that $\mathcal{A}$ is ∞-conservative, it suffices to show that $\mathcal{A}$ is conservative and closed under self-composition, as reflected in the following definition.

Definition 2. *$\mathcal{A} \subseteq \mathcal{V}(\mathbb{R}^n)$ is closed under self-composition if for all $V \in \mathcal{A}$ and $k \geq 1$, $V^k \in \mathcal{A}$.*

This leads us to the following specialization of Question 1.

Question 2. *Let $\mathcal{A} \subseteq \mathcal{V}(\mathbb{R}^n)$ be conservative. Is $\mathcal{A}$ closed under self-composition?*

Vector Fields and Optimization. Motivated by optimization, we will often consider vector fields of the form $V(x) = \nabla f(x)$, where $f : \mathbb{R}^n \to \mathbb{R}$ is differentiable. Given $\mathcal{F} \subseteq \mathcal{D}(\mathbb{R}^n, \mathbb{R})$, we define $\nabla \mathcal{F} = \{V \in \mathcal{V}(\mathbb{R}^n) : V = \nabla f, f \in \mathcal{F}\}$. For $\gamma \in \mathbb{R}$, we define $I - \gamma\nabla\mathcal{F} := \{I - \gamma\nabla f : f \in \mathcal{F}\}$. A recurring theme in this work is whether a set $I - \gamma\nabla\mathcal{F}$ is k-conservative. Such vector fields arise naturally in optimization, as gradient descent on a function f with learning rate γ corresponds to the discrete-time dynamical system given by $x_{t+1} = (I - \gamma\nabla f)(x_t)$.

Given an initial point x_0, the iterates of gradient descent then satisfy $x_k = V^k(x_0)$ where $V = I - \gamma\nabla f$. Therefore, if $I - \gamma\nabla f$ is ∞-conservative, then the k-th iterate of gradient descent is actually $\nabla h_k(x_0)$ for some function $h_k : \mathbb{R}^n \to \mathbb{R}$. In general, this viewpoint will allow us to understand the behavior of optimization algorithms by analyzing properties of the functions h_k.

2 Connections to Federated Learning

Questions about whether a vector field is k-conservative have important implications for federated learning, one noteworthy approach to which is *federated averaging* (FedAvg) [9]. A slightly simplified version of FedAvg operates as follows. Suppose we have clients $c = 1, 2, \ldots, C$, each with loss function $f_c : \mathbb{R}^n \to \mathbb{R}$. At each round, the server broadcasts its model the clients. The clients perform k steps of gradient descent (with learning rate γ) on their loss functions, and send the resulting models to the server. The server updates its model as the average of these client models. Since communication from clients to the server is often a bottleneck [1, 9], this algorithm is often practical only when $k > 1$. When $k = 1$, this is equivalent to gradient descent with learning rate γ on the average of the client loss functions.

More formally, let $V_c := I - \gamma\nabla f_c$. At each round t, each client computes $V_c^k(x_t)$, and the server updates its model via $x_{t+1} = C^{-1}\sum_{c=1}^C V_c^k(x_t)$. This "operator-theoretic" view of FedAvg has been previously used to leverage techniques from operator theory to analyze and design federated learning algorithms [7, 8, 12]. In order to allow the server to determine the magnitude of its update at each step, [13] introduces a "model delta" version of FedAvg. This corresponds to the server update

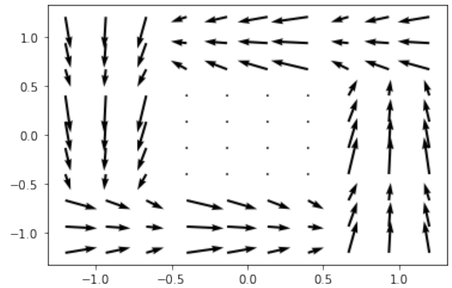
$$x_{t+1} = x_t - \frac{\eta}{C}\sum_{c=1}^C \left(x_t - V_c^k(x_t)\right) \tag{1}$$

where $\eta > 0$ is the server learning rate, which we may set to 1 to recover the average of the client models. In the sequel we let FedAvg denote the update rule in (1). If we let V_s be the "server" vector field given by

$$V_s = \frac{1}{C}\sum_{c=1}^C (I - V_c^k) \tag{2}$$

then (1) is equivalent to $x_{t+1} = x_t - \eta V_s(x_t)$. This leads us to our guiding observation: If each V_c is k-conservative, then V_s is an average of conservative vector fields and is conservative as well. Therefore, there is some function f_s such that $\nabla f_s = V_s$, and the dynamics of FedAvg are then equivalent to the dynamics of gradient descent on the function f_s (see Theorem 3 for a formal statement of this). This allows us to reduce the behavior of FedAvg to the behavior of gradient descent on this "surrogate loss" f_s. Such an approach was used in [3] to understand the dynamics of FedAvg and related methods on quadratic functions. In this work, we consider more general functions, including convex and non-convex functions.

Figure 1: Non-conservative server vector field V_s induced by f_1, f_2 in (3) for k sufficiently large.



2.1 Non-Conservative Dynamics in Federated Learning

As we sketched in the section above (and formalize in Section 5.1), when the vector fields $I - \gamma\nabla f_c$ are k-conservative, FEDAVG with k local steps behaves identically to gradient descent on some surrogate loss function. On the other hand, in this section we show that without k-conservatism, FEDAVG can demonstrate fundamentally non-conservative behavior, making its dynamics distinct from those of gradient descent. Notably, this can occur even when $C = 2$ and there is no stochasticity whatsoever. For example, for $c \in \{1, 2\}$, consider the client loss functions

$$f_c(x, y) := f_c^{(1)}(x, y) + f_c^{(2)}(x, y) \tag{3}$$

where

$$f_c^{(1)}(x, y) := \min\left(\frac{\alpha_c}{2}(y - y_c)^2 + \frac{\beta_c}{2}(x - x_c)^2, 1\right),$$
$$f_c^{(2)}(x, y) := \min\left(\frac{\alpha_c}{2}(y + y_c)^2 + \frac{\beta_c}{2}(x + x_c)^2, 1\right).$$

Notably, $I - \gamma\nabla f_c$ may not be k-conservative for $k > 1$. As we show in Appendix C, for some choice of $\alpha_c, \beta_c \in \mathbb{R}$, $x_c, y_c \in \mathbb{R}^2$ (for $c = 1, 2$), $\gamma > 0$ and k sufficiently large, the resulting server vector field V_s in (2) is non-conservative.

To illustrate this, in Fig. 1 we plot this server vector field V_s. Running FEDAVG with appropriate initialization over the 2-client setup in Appendix C follows the vector field V_s, and cycles endlessly (see Fig. 2 in Appendix C). In short, FEDAVG may behave badly in the absence of k-conservatism.

3 Examples of k-Conservative Vector Fields

We now give concrete examples of k-conservative vector fields. These include vector fields associated to linear and logistic regression. Let $\mathcal{P}_d(\mathbb{R}^n, \mathbb{R}^m)$ denote the subset of $\mathcal{V}(\mathbb{R}^n, \mathbb{R}^m)$ whose coordinate functions are homogeneous polynomials of degree d. We abbreviate this as $\mathcal{P}_d(\mathbb{R}^n)$ when $n = m$.

Constant Vector Fields. The space $\mathcal{P}_0(\mathbb{R}^n)$ of constant vector fields is clearly closed under self-composition. Constant vector fields are conservative, so $\mathcal{P}_0(\mathbb{R}^n)$ is ∞-conservative.

Affine Vector Fields. Let $\mathcal{A}(\mathbb{R}^n)$ be the set of affine vector fields in $\mathcal{V}(\mathbb{R}^n)$. This consists of all V of the form $V(x) = Ax + b$ for $A \in \mathbb{R}^{n\times n}$, $b \in \mathbb{R}^n$. Let $\mathcal{S}(\mathbb{R}^n)$ denote the set of such V where A is symmetric. If $V \in \mathcal{A}(\mathbb{R}^n)$ is conservative, it is the gradient of some quadratic function. Simple algebraic manipulation then implies that V is conservative iff A is symmetric. Since $\mathcal{S}(\mathbb{R}^n)$ is closed under self-composition, $\mathcal{S}(\mathbb{R}^n)$ is ∞-conservative while $\mathcal{A}(\mathbb{R}^n)$ is not conservative. In particular, if f is a quadratic function, ∇f and $I - \gamma\nabla f$ are both ∞-conservative.

Continous Univariate Functions. Consider the set $\mathcal{C}^0(\mathbb{R})$ of continuous functions from $\mathbb{R}$ to $\mathbb{R}$. By elementary analysis, $\mathcal{C}^0(\mathbb{R})$ is closed under self-composition, and by the fundamental theorem of calculus, it is conservative. Thus, $\mathcal{C}^0(\mathbb{R})$ is ∞-conservative.

More generally, let $\mathcal{C}^0(\mathbb{R})^n$ denote the subset of $\mathcal{V}(R^n)$ containing vector fields of the form

$$V(x_1, \ldots, x_n) = (f_1(x_1), f_2(x_2), \ldots, f_n(x_n))$$

where $f_1, \dots, f_n \in \mathcal{C}^0(\mathbb{R})$. Then note that $V(x_1, \dots, x_n) = \nabla\left(\sum_{i=1}^n \int_0^{x_i} f_i(t)dt\right)$ so $\mathcal{C}^0(\mathbb{R})^n$ is conservative. Since $\mathcal{C}^0(\mathbb{R})^n$ is closed under self-composition, it is also ∞-conservative.

Non-example: Cubic Polynomials. Let $f(x, y) = x^2 y$. By direct computation,

$$(\nabla f)^2(x, y) = \begin{pmatrix} 4x^3 y \\ 4x^2 y^2 \end{pmatrix} =: \begin{pmatrix} h_1(x, y) \\ h_2(x, y) \end{pmatrix}.$$

We then have $\frac{\partial}{\partial y} h_1(x, y) = 4x^3$, $\frac{\partial}{\partial x} h_2(x, y) = 8xy^2$. By Clairaut's theorem (see [14, Chapter 4]), $(\nabla f)^2$ is not conservative. Thus, $\nabla \mathcal{P}_3(\mathbb{R}^2, \mathbb{R})$ is conservative but not 2-conservative.

3.1 Gradient Vector Fields of Generalized Linear Models

Let $\mathcal{G} \subsetneq \mathcal{C}^1(\mathbb{R}^n, \mathbb{R})$ denote the class of functions of the form

$$f(x) = \sum_{i=1}^m \sigma(\langle x, z_i \rangle) \tag{4}$$

where m is a positive integer, $z_i \in \mathbb{R}^n$, and $\sigma \in \mathcal{C}^1(\mathbb{R})$. Such functions arise in statistics and optimization when considering generalized linear models. For example, when $\sigma(t) = \ln(1 + e^{-t})$, (4) is effectively the loss function used in logistic regression.

We further define $\mathcal{G}_\perp \subsetneq \mathcal{G}$ to be the set of functions of the form (4) where $\{z_i\}_{i=1}^m$ are mutually orthogonal. We then have the following result.

Theorem 1. *Let $f \in \mathcal{G}_\perp$ be as in (4). Let $\phi_i(t) = \|z_i\|^2 \sigma'(t)$. For all $k \geq 2$,*

$$(\nabla f)^k(x) = \nabla\left(\sum_{i=1}^m \int_0^{\langle x, z_i \rangle} \sigma'(\phi_i^{k-1}(t))dt\right). \tag{5}$$

Thus, $\nabla \mathcal{G}_\perp$ is ∞-conservative and closed under self-composition.

In order to understand the dynamics of gradient descent on generalized linear models, we now extend Theorem 1 to the function class $I - \gamma \nabla \mathcal{G}_\perp$.

Theorem 2. *Let $f \in \mathcal{G}_\perp$ be as in (4). For fixed $\gamma \in \mathbb{R}$, let $\psi_i(t) = t - \gamma \|z_i\|^2 \sigma'(t)$. For all $k \geq 2$,*

$$(I - \gamma \nabla f)^k(x) = x - \gamma \nabla\left(\sum_{i=1}^m \int_0^{\langle x, z_i \rangle} \sigma'(\psi_i^{k-1}(t))dt\right). \tag{6}$$

Thus, $I - \gamma \nabla \mathcal{G}_\perp$ is ∞-conservative and closed under self-composition.

On the other hand, $\nabla \mathcal{G}$ is not 2-conservative. Let $f_1(x, y) = e^x$, $f_2(x, y) = e^{x+y}$, $f_3 = f_1 + f_2$. Note that by Theorem 1, $\nabla f_1, \nabla f_2$ are both ∞-conservative. However, by direct computation

$$(\nabla f_3)^2(x, y) = \begin{pmatrix} \exp(e^x + e^{x+y}) + \exp(e^x + 2e^{x+y}) \\ \exp(e^x + 2e^{x+y}) \end{pmatrix} =: \begin{pmatrix} h_1(x, y) \\ h_2(x, y) \end{pmatrix}.$$

One can then verify that $\frac{\partial}{\partial y} h_1(x, y) \neq \frac{\partial}{\partial x} h_2(x, y)$, so by Clairaut's theorem, ∇f_3 is not 2-conservative. Notably, f_1, f_2 and f_3 are all convex functions, demonstrating that whether $\nabla \mathcal{F}$ is ∞-conservative is not determined by whether the class $\mathcal{F}$ is convex.

Finally, we note that it is not clear whether there are ∞-conservative vector fields in $\nabla \mathcal{G} \backslash \nabla \mathcal{G}_\perp$. Exactly characterizing the set of ∞-conservative vector fields in $\nabla \mathcal{G}$ remains open.

4 Smooth k-Conservative Vector Fields

We now explicitly construct the space of smooth, k-conservative vector fields. Given $V \in \mathcal{C}^\infty(\mathbb{R}^n)$, let $J(V) : \mathbb{R}^n \to \mathbb{R}^{n \times n}$ denote its Jacobian, which we can view as an $n \times n$ matrix over $\mathcal{C}^\infty(\mathbb{R}^n, \mathbb{R})$. If $V \in \mathcal{C}^\infty(\mathbb{R}^n)$, then by the Poincaré lemma (see [16, Section 4.18] for reference), V is k-conservative if and only if $J(V^k)$ is symmetric. For $k \geq 1$, we then define $D_k : \mathcal{C}^\infty(\mathbb{R}^n) \to \mathcal{C}^\infty(\mathbb{R}^n, \mathbb{R}^{n \times n})$ by

$$D_k(V) := J(V^k) - J(V^k)^\intercal. \tag{7}$$

Thus, $V \in \mathcal{C}^\infty(\mathbb{R}^n)$ is k-conservative if and only if $D_k(V) = 0$. We may now define the space of smooth, k-conservative vector fields by $\mathcal{W}^k(\mathbb{R}^n) := D_k^{-1}(\{0\})$ and $\mathcal{W}^\infty(\mathbb{R}^n) := \cap_{k=1}^\infty \mathcal{W}^k(\mathbb{R}^n)$. We note a few facts about $\mathcal{W}^\infty(\mathbb{R}^n)$:

1. $W^k(\mathbb{R}^n)$ and $\mathcal{W}^\infty(\mathbb{R}^n)$ are closed in $\mathcal{C}^\infty(\mathbb{R}^n)$ under several natural topologies, like that of uniform convergence of all derivatives on compact sets. To see this, note that D_k is a continuous function in this topology, so $D_k^{-1}(\{0\}) = W^k(\mathbb{R}^n)$ is closed. Thus, $\mathcal{W}^\infty(\mathbb{R}^n)$ is an intersection of closed sets, and is closed itself.
2. $\mathcal{W}^\infty(\mathbb{R}^n)$ is closed under scalar multiplication. While it contains linear subspaces (such as the space of symmetric linear vector fields, see Section 3), it is not closed under addition. For a simple counter-example, see the end of Section 3.1.
3. While $\mathcal{W}^\infty(\mathbb{R}^n)$ is closed under self-composition, it is not closed under arbitrary composition. See Appendix A for an explicit counter-example.

Some basic open questions on the structure of $\mathcal{W}^\infty(\mathbb{R}^n)$:

1. How does $\mathcal{W}^k(\mathbb{R}^n)$ relate to $\mathcal{W}^j(\mathbb{R}^n)$ for $k \neq j$? As we show in Appendix A, $\mathcal{W}^k(\mathbb{R}^n) \not\subseteq \mathcal{W}^j(\mathbb{R}^n)$ for $j < k$. More generally, are there smooth vector fields that are k-conservative but not j-conservative for $j \neq k$?
2. If we restrict to $\mathcal{P}_d(\mathbb{R}^n)$, the zero locus of D_k defines a projective variety over the coefficients of polynomials in $\mathcal{P}_d(\mathbb{R}^n)$. For example, applying Eq. (7) to $\mathcal{P}_d(\mathbb{R}^n)$, we find:
   - $\mathcal{W}^1(\mathbb{R}^n) \cap \mathcal{P}_1(\mathbb{R}^n)$ is a hyperplane.
   - $\mathcal{W}^2(\mathbb{R}^2) \cap \mathcal{P}_1(\mathbb{R}^2)$ is a union of two hyperplanes.
   - $\mathcal{W}^3(\mathbb{R}^2) \cap \mathcal{P}_1(\mathbb{R}^2)$ is a union of a hyperplane and a quadric surface.
   - $\mathcal{W}^1(\mathbb{R}^2) \cap \mathcal{W}^2(\mathbb{R}^2) \cap \mathcal{P}_2(\mathbb{R}^2)$ is a quadric surface.

   See Appendix A for the full details on these computations. Can we say anything more general? For example, what is the degree of $\mathcal{W}^k(\mathbb{R}^n) \cap \mathcal{P}_d(\mathbb{R}^n)$?

5 Implications for Optimization

In this section, we show that k-conservatism has important ramifications for optimization. We first show that if f is a smooth function and ∇f is ∞-conservative, then functions g_k with $\nabla g_k = (\nabla f)^k$ inherit many geometric properties of f. Due to their importance in optimization, we focus on notions of convexity. When f is smooth, we can reduce such properties to questions about eigenvalues of Jacobian matrices. We first bound the Jacobian eigenvalues of iterated vector fields.

Proposition 1. *Suppose $f \in \mathcal{C}^\infty(\mathbb{R}^n, \mathbb{R})$ and ∇f is j-conservative for $1 \leq j \leq k$, with $(\nabla f)^j = \nabla g_j$. Then for all such j, the function g_j is smooth and satisfies:*

1. *Suppose there are $\alpha, \beta \geq 0$ such that for all x, $\alpha I \preceq J(\nabla f)(x) \preceq \beta I$. Then for all x,*
$$\alpha^k I \preceq J(\nabla g_j)(x) \preceq \beta^k I.$$
2. *Suppose there is some $\lambda \geq 0$ such that for all x, $-\lambda I \preceq J(\nabla f)(x) \preceq \lambda I$. Then for all x,*
$$-\lambda^k I \preceq J(\nabla g_j)(x) \preceq \lambda^k I.$$

Items 1 and 2 also hold if we change $\preceq$ to $\prec$ throughout.

We will use Proposition 1 to show that iterating ∞-conservative vector fields preserves geometric properties, including Lipschitz continuity, as in the following definition.

Definition 3. *A vector field $V \in \mathcal{C}^1(\mathbb{R}^n)$ is β-Lipschitz continuous if for all $x \in \mathbb{R}^n$, $\|J(V)(x)\| \leq \beta$. V is Lipschitz continuous if there is some β for which V is β-Lipschitz continuous.*

In the definition above, $\|\cdot\|$ refers to the operator norm induced by the ℓ_2 norm on $\mathbb{R}^n$, viewing $J(V)(x)$ as an $n \times n$ matrix over $\mathbb{R}$. In the following, we let $\mathcal{L}(\mathbb{R}^n) \subsetneq \mathcal{V}(\mathbb{R}^n)$ denote the set of Lipschitz continuous vector fields. Proposition 1 directly implies the following result.

Corollary 1. *Let $\mathcal{F} \subsetneq \mathcal{C}^\infty(\mathbb{R}^n, \mathbb{R})$ be the set of (a) smooth, strongly convex functions, (b) smooth, strictly convex functions, or (c) smooth, convex functions. Then $\nabla\mathcal{F} \cap \mathcal{W}^\infty(\mathbb{R}^n)$ and $\nabla\mathcal{F} \cap \mathcal{W}^\infty(\mathbb{R}^n) \cap \mathcal{L}(\mathbb{R}^n)$ are closed under self-composition.*

Thus, we see that convexity "lifts" under self-composition of the associated gradient vector field: If f is smooth, convex, and ∇f is k-conservative, then $(\nabla f)^k = \nabla g$ for some smooth, convex function g.

Next, we consider vector fields $V = I - (I - \gamma\nabla f)^k$ where $\gamma > 0$ (induced by gradient descent). In the following lemma, we show that if V is ∞-conservative and $V^k = \nabla h_k$, then h_k inherits smoothness and critical points from f.

Lemma 1. *Let $f \in \mathcal{C}^\infty(\mathbb{R}^n, \mathbb{R})$ and $\gamma \in \mathbb{R}_{>0}$. Suppose that $(I - \gamma\nabla f)$ is j-conservative for $1 \leq j \leq k$. Then $V_k := I - (I - \gamma\nabla f)^k$ is conservative, and if $\nabla h_k = V_k$ then (1) h_k is smooth, and (2) if $\nabla f(y) = 0$, then $\nabla h_k(y) = 0$.*

In fact, many geometric properties important to optimization (such as convexity) are also inherited by h_k, provided that γ is not too large, as in the following.

Lemma 2. *Suppose $f \in \mathcal{C}^\infty(\mathbb{R}^n, \mathbb{R})$ and ∇f is β-Lipschitz continuous. Suppose that for some $\gamma \in \mathbb{R}_{>0}$, $(I - \gamma\nabla f)$ is j-conservative for $1 \leq j \leq k$, with $\nabla h_k = I - (I - \gamma\nabla f)^k$. Then:*

1. *If f is α-strongly convex and $\gamma \leq 2(\alpha+\beta)^{-1}$ then h_k is $(1-\lambda^k)$-strongly convex and ∇h_k is $(1+\lambda^k)$-Lipschitz continuous for $\lambda = 1 - \gamma\alpha$.*
2. *If f is convex and $\gamma \leq 2\beta^{-1}$ then h_k is convex and ∇h_k is 2-Lipschitz continuous. If $\gamma \leq \beta^{-1}$, then ∇h_k is 1-Lipschitz continuous.*
3. *If f is strictly convex and $\gamma < 2\beta^{-1}$ then h_k is strictly convex.*
4. *If f is δ-weakly convex for $\delta \leq \beta$ and $\gamma \leq 2\beta^{-1}$, then h_k is $(\lambda^k - 1)$-weakly convex and ∇h_k is $(1+\lambda^k)$-Lipschitz continuous for $\lambda = 1 + \gamma\delta$.*

5.1 Convergence Rates of FedAvg

We now use our machinery above to understand the convergence of FedAvg in various settings. Recall that the server update at each round is given by $x_{t+1} = x_t - \eta V_s(x_t)$, where the "server vector field" V_s is given by (2). Throughout, we assume that each client c performs k steps of gradient descent with learning rate $\gamma > 0$ on their loss function f_c. We make the following assumption.

Assumption 1. *For all c, $f_c \in \mathcal{C}^\infty(\mathbb{R}^n, \mathbb{R})$ and $I - \gamma\nabla f_c$ is j-conservative for $1 \leq j \leq k$.*

This leads to the following result on sufficient conditions for V_s to be conservative.

Theorem 3. *Under Assumption 1, V_s is a conservative vector field. Moreover, if $V_s = \nabla f_s$, then f_s is smooth and the FedAvg server update in (1) is equivalent to the following gradient descent step:*

$$x_{t+1} = x_t - \eta\nabla f_s(x_t). \tag{8}$$

In this setting, if we have some understanding of f_s (for example, whether f_s is convex), we can immediately apply centralized optimization results to derive convergence results for FedAvg. To better understand the structure of f_s, we will use Lemma 2. Since this requires Lipschitz continuity, we make the following assumption.

Assumption 2. *For all c, ∇f_c is β-Lipschitz continuous.*

Under Assumptions 1 and 2, Lemma 2 lifts geometric properties of the f_c to f_s. Combining this with Theorem 3, we can translate convergence rates for gradient descent to convergence rates for FedAvg in strongly convex and convex settings. We make no direct assumptions on client heterogeneity. Throughout, we let f_s be a function such that $V_s = \nabla f_s$, as guaranteed by Theorem 3.

Theorem 4. *Suppose Assumptions 1 and 2 hold, and that for all c, f_c is α-strongly convex. Then f_s has a unique minimizer x_s^*, and if $\gamma = 2(\alpha+\beta)^{-1}$, $\eta = 1$, the iterates $\{x_t\}_{t=0}^\infty$ of FedAvg satisfy*

$$\|x_t - x_s^*\| \leq \left(\frac{\beta - \alpha}{\beta + \alpha}\right)^{kt} \|x_0 - x_s^*\|. \tag{9}$$

Proof. This follows directly from combining Theorem 3 and Lemma 2 with well-known convergence rates for smooth, strongly convex functions (for example, see [2, Theorem 3.10]). □

The convergence rate in (9) was shown first in [8, Theorem 2.11], which extended to non-conservative gradient vector fields. The salient difference is that under under our assumptions, the limit point x_s^* is actually the global minimizer of some strongly convex function. As we discuss below, this allows us to immediately derive analogous results for variants of FEDAVG that apply other server optimizers.

When $k = 1$, this recovers the convergence of gradient descent on $f_{avg} = C^{-1}\sum_{c=1}^{C} f_c$. Hence, FEDAVG with $k > 1$ yields an exponential improvement in convergence (with respect to k), but may not converge to the minimizer x^* of f_{avg}. To understand this discrepancy, one could analyze $\|x_s^* - x^*\|$. A tight upper bound was given for strongly convex quadratic functions in [3, Lemma 5]. A bound in the general strongly convex setting (not assuming k-conservatism) was given in [8, Theorem 2.14], though whether this bound can be improved under Assumption 1 is an open question.

We now give a convergence rate for FEDAVG in the convex setting.

Theorem 5. *Suppose Assumptions 1 and 2 hold, and that for all c, f_c is convex with finite minimizer. Then f_s has a finite minimizer x_s^*, and if $\gamma = \beta^{-1}$, $\eta = 1$, the iterates $\{x_t\}_{t=0}^{\infty}$ of* FEDAVG *satisfy*

$$f_s(x_t) - f_s(x_s^*) \leq \frac{1}{2t}\|x_0 - x_s^*\|^2. \tag{10}$$

Proof. This follows directly from combining Theorem 3 and Lemma 2 with well-known convergence rates for smooth, convex functions (for example, see [2, Theorem 3.3]). □

To the best of our knowledge, Theorem 5 is the first result showing that FEDAVG exhibits convergent behavior on a class of functions, even with fixed learning rates and $k > 1$. Unlike Theorem 4, it is not clear that the convergence in (10) is "faster" (in some sense) than the convergence of gradient descent on f_{avg}. Such analysis is an open and important problem.

These techniques allow us to transfer convergence rates for many optimization algorithms to federated learning under the same assumptions as Theorems 4 and 5; We can directly analyze any federated learning algorithm where the server gradient descent step in (1) is replaced with another optimizer (as proposed in [13]). For example, using SGD with momentum [5] or adaptive methods such as Adagrad [4, 10] can lead to improved empirical convergence [13]. Notably, our framework can be used directly to show that in the strongly convex setting, methods such as Nesterov momentum accelerate convergence to x_s^*.

6 Open Problems

As we have shown, FEDAVG is well-behaved when certain vector fields are k-conservative (Theorems 4 and 5) and can exhibit non-convergent, circular behavior when they are not (Section 2.1). Better characterizations of when FEDAVG exhibits convergent behavior (or fails to do so) is an important open problem. Similarly, we have only scratched the surface on how the dynamics of the client loss functions lift to the server dynamics. While many convexity-adjacent properties lift (Lemma 2), one can show that many natural properties (including being bounded below) do not lift. What about properties such as the Polyak-Łojasiewicz condition [6]? More generally, which properties lift, and can we understand the behavior of FEDAVG on some class of non-convex functions?

Another important area is understanding the empirical effectiveness of methods such as FEDAVG. As discussed in [15], theoretical convergence rates of federated learning methods often do not improve upon centralized rates for algorithms such as gradient descent. While Theorem 4 shows that FEDAVG accelerates convergence to a non-optimal point, it is unclear whether Theorem 5 implies a similar acceleration. More generally, is there some sense in which the limit point x_s^* is a useful point of convergence, either for learning a global model, or as a starting point for personalization?

Finally, the non-conservative dynamics presented in Section 2.1 point to a fundamental failure of methods such as FEDAVG. This mirrors non-conservative dynamics arising from many GAN training methods [11]. Can we use insights from training multi-agent systems (such as GANs) to create better federated learning methods, or even to simply design better client loss functions?

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A In-Depth Examples

In this section, we give some in-depth examples regarding the k-conservatism of vector fields in $\mathcal{C}^\infty(\mathbb{R}^2)$. Note that for $V \in \mathcal{C}^\infty(\mathbb{R}^2)$, $D_k(V)$ (defined in (7)) is a 2×2 anti-symmetric matrix over $\mathcal{C}^\infty(\mathbb{R}^2, \mathbb{R})$. Thus, when setting $D_k(V) = 0$, it suffices to consider a single off-diagonal entry. In a slight abuse of notation, in this section we will identify $D_k(V)$ with either off-diagonal entry of $D_k(V)$. Note that this is well-defined up to a factor of -1.

A.1 Linear Vector Fields

Recall that $\mathcal{P}_1(\mathbb{R}^n)$ denotes the set of linear vector fields. Let $V \in \mathcal{P}_1(\mathbb{R}^n)$ be of the form $V(x, y) = (ax + by, cx + dy)$. Then we have the following equations (where we consider only the non-zero off-diagonal entries of D_k):

$$
\begin{aligned}
D_1(V) &= b - c \\
D_2(V) &= (b - c)(a + d) \\
D_3(V) &= (b - c)(a^2 + ad + bc + d^2) \\
D_4(V) &= (b - c)(a + d)(a^2 + 2bc + d^2).
\end{aligned}
$$

If V is conservative, then $b = c$ and these equations all vanish. Comparing D_1, D_2, and D_3, we see that 2-conservative vector fields need not be conservative nor 3-conservative. For example, if we take

$$
V(x) = \begin{pmatrix} 1 & 2 \\ 1 & -1 \end{pmatrix} x
$$

then V is 2-conservative and 4-conservative, but not conservative or 3-conservative.

Recall that in Section 3, we defined $\mathcal{S}_1(\mathbb{R}^n)$ to be the set of symmetric linear vector fields. While $\mathcal{S}_1(\mathbb{R}^n)$ is closed under self-composition, it is not closed under arbitrary composition. is To see this, consider the symmetric linear vector fields

$$
V_1(x) = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} x, \quad V_2(x) = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} x.
$$

Then $V_1, V_2 \in \mathcal{W}^\infty(\mathbb{R}^n)$. However, $V_1 \circ V_2 \notin \mathcal{W}^\infty(\mathbb{R}^n)$ since

$$
V_1(V_2(x)) = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix} x
$$

which is a non-symmetric linear map.

Notably, $\mathcal{P}_1(\mathbb{R}^n)$ contains vector fields that are j-conservative but not k-conservative for $k < j$. For $j \geq 2$, consider the vector field given by $V_j(x) = A_j x$ where

$$
A_j(x) = \begin{pmatrix} \cos(\theta_j) & \sin(\theta_j) \\ -\sin(\theta_j) & \cos(\theta_j) \end{pmatrix}, \quad \theta_j = \frac{\pi}{j}.
$$

This is the vector field that rotates vectors by an angle of π/j. Since V_j^k is conservative precisely when V_j^k is symmetric, V_j^k is conservative if and only if $\sin(k\theta_j) = 0$. Thus, V_j is k-conservative if and only if j divides k‘.

A.2 Gradient Vector Fields of Cubic Polynomials

Consider the vector space $\mathcal{P}_3(\mathbb{R}^2, \mathbb{R})$ containing polynomials of the form

$$
f(x, y) = ax^3 + bx^2y + cxy^2 + dy^3
$$

for $a, b, c, d \in \mathbb{R}$. All such f satisfy $D_1(\nabla f) = 0$. By direct computation, taking only the off-diagonal entries of D_k, we get

$$
D_2(\nabla f) = g_1 x^3 + g_2 x^2 y + g_3 x y^2 + g_4 y^3.
$$

for $g_1, g_2, g_3, g_4 \in \mathbb{R}[a, b, c, d]$ defined by

$$\begin{aligned}
g_1 &= -4b(3ac - b^2 + 3bd - c^2) \\
g_2 &= 4(3a - 2c)(3ac - b^2 + 3bd - c^2) \\
g_3 &= 4(2b - 3d)(3ac - b^2 + 3bd - c^2) \\
g_4 &= 4c(3ac - b^2 + 3bd - c^2).
\end{aligned}$$

One can then verify that these equations vanish simultaneously if and only if

$$g(a, b, c, d) = 3ac - b^2 + 3bd - c^2 = 0.$$

Thus, the set of 2-conservative functions in $\nabla\mathcal{P}_3(\mathbb{R}^2, \mathbb{R})$ is the hypersurface given by the zero locus of g. Since this zero locus is not closed under addition, the set of 2-conservative vector fields in $\nabla\mathcal{P}_3(\mathbb{R}^2, \mathbb{R})$ is not closed under addition either.

An analogous computation shows that the set of 3-conservative function is given by the zero locus of 8 homogeneous polynomials of degree 7, each of which is divisible by g. Therefore, all 2-conservative vector fields in $\nabla\mathcal{P}_3(\mathbb{R}^2, \mathbb{R})$ are also 3-conservative.

B Omitted Proofs

B.1 Proof of Theorem 1

Proof. Let $V = \nabla f$. We claim that for all $k \geq 1$,

$$V^k(x) = \sum_{i=1}^{m} \sigma'(\phi_i^{k-1}(\langle x, z_i \rangle)) z_i$$

where ϕ_i^0 is the identity function. We will show this inductively. This clearly holds for $k = 1$. By the inductive hypothesis, we then have

$$\begin{aligned}
V^{k+1}(x) &= \sum_{i=1}^{m} \sigma'(\langle V^k(x), z_i \rangle) z_i \\
&= \sum_{i=1}^{m} \sigma'\left(\left\langle \sum_{j=1}^{m} \sigma'(\phi_i^{k-1}(\langle x, z_j \rangle)) z_j, z_i \right\rangle \right) z_i \\
&= \sum_{i=1}^{m} \sigma'\left(\|z_i\|^2 \sigma'(\phi_i^{k-1}(\langle x, z_i \rangle)) \right) z_i \\
&= \sum_{i=1}^{m} \sigma'(\phi_i^k(\langle x, z_i \rangle)) z_i.
\end{aligned}$$

Here, the second equality follows from the inductive hypothesis, while the third equality follows from the orthogonality of the z_i. Therefore, if we define $h_k : \mathbb{R} \to \mathbb{R}$ via

$$h_k(x) = \sum_{i=1}^{m} \int_0^{\langle x, z_i \rangle} \sigma'(\phi_i^{k-1}(t)) dt$$

then by the chain rule,

$$\nabla h_k(x) = \sum_{i=1}^{m} \sigma'(\phi_i^{k-1}(\langle x, z_i \rangle)) z_i = V^k(x).$$

□

B.2 Proof of Theorem 2

Proof. The proof is nearly identical to the proof of Theorem 1. Let $V(x) = x - \gamma \nabla f(x)$. A slight modification of the inductive argument in the proof of Theorem 1 implies that

$$V^k(x) = x - \gamma \sum_{i=1}^{m} \sigma'(\psi_i^{k-1}(\langle x, z_i \rangle)) z_i.$$

By the chain rule, this implies that

$$V^k(x) = x - \gamma \nabla \left(\sum_{i=1}^{m} \int_0^{\langle x, z_i \rangle} \sigma'(\psi_i^{k-1}(t)) dt \right).$$

□

B.3 Proof of Proposition 1

Proof. Since f is smooth, $(\nabla f)^j \in \mathcal{C}^\infty(\mathbb{R}^n)$. Since $(\nabla f)^j = \nabla g_j$ (and in particular, g_j is differentiable), we must have $g_j \in \mathcal{C}^\infty(\mathbb{R}^n, \mathbb{R})$.

For Item 1, we proceed inductively. For $k = 1$, the result holds by assumption. For the inductive step, let $2 \leq k \leq K$, and assume the result holds for $k - 1$. Let $J_j(x)$ denote the Jacobian of ∇g_j at a point x. By the chain rule,

$$J_j(x) = J_1(\nabla g_{j-1}(x)) J_{j-1}(x). \tag{11}$$

By the inductive hypothesis, we have

$$\alpha^{j-1} I \preceq J_{j-1}(x) \preceq \beta^{j-1} I$$

and by our assumptions on ∇f, we have

$$\alpha I \preceq J_1(\nabla g_{j-1})(x) \preceq \beta I.$$

Since $J_j(x)$ is symmetric (as it is the Jacobian of a gradient field), its eigenvalues are therefore products of eigenvalues of $J_{j-1}(x)$ and $J_1(\nabla g_{j-1})(x)$. Hence, its maximum eigenvalue is at most β^j, and its minimum eigenvalue is at most α^j.

The proof of Item 2 follows in a similar way, noting that by the inductive hypothesis, the matrices on the right-hand side of (11) will have eigenvalues in the ranges of $[-\lambda, \lambda]$ and $[-\lambda^{j-1}, \lambda^{j-1}]$. Since $J_j(x)$ is symmetric, its eigenvalues are products of the eigenvalues of the matrices in the right-hand side of (11), and the result follows. □

Remark. *Note the critical role of symmetry in the argument above. In $\mathbb{R}^n$, $J(V^k)$ is symmetric if and only if V is k-conservative. Thus, k-conservatism is exactly the condition required for us to reason about how the eigenvalues of $J(V^k)$ relate to that of $J(V)$.*

B.4 Proof of Corollary 1

Proof. This follows directly from Proposition 1. In particular, for (1), if f is smooth and strongly convex, then there is some positive α such that $\alpha I \preceq J(\nabla f)(x)$ for all x. Since $\nabla f \in \mathcal{W}^\infty(\mathbb{R}^n)$, for all $k \geq 1$, there is some g_k such that $\nabla g_k = (\nabla f)^k$. By Proposition 1, we have $\alpha^k I \preceq J(\nabla g_k)(x)$, so g_k is smooth and strongly convex. If ∇f is also Lipschitz continuous, then there is some β for which $J(\nabla f)(x) \preceq \beta I$ for all x, and a similar argument shows that $\alpha^k I \preceq J(\nabla g_k)(x) \preceq \beta^k I$.

The case of convex or strictly convex follows in an analogous manner, as they correspond (respectively) to the bounds $0 \preceq J(\nabla f)(x)$ and $0 \prec J(\nabla f)(x)$ (for all x), which is also preserved under k-fold composition by Proposition 1. □

B.5 Proof of Lemma 1

Proof. For (1), h_k is clearly differentiable. Moreover, $\nabla h_k = V_k \in \mathcal{C}^\infty(\mathbb{R}^n)$, as smoothness is preserved under addition and composition. Hence, $h_k \in \mathcal{C}^\infty(\mathbb{R}^n, \mathbb{R})$. For (2), note that $(I - \nabla f)(y) = y - \nabla f(y) = y$. Therefore, $\nabla h_k(y) = y - (I - \nabla f)^k(y) = y - y = 0$. □

B.6 Proof of Lemma 2

Proof. This is a direct consequence of Proposition 1. For (1), by assumption we have $\alpha I \preceq J(\nabla f)(x) \preceq \beta I$ for all x, and therefore $-\lambda \preceq J(I - \gamma \nabla f)(x) \preceq \lambda I$ for all x where $\lambda = 1 - \gamma\alpha$. By Proposition 1, we have that for all x

$$-\lambda^k I \preceq J((I - \gamma \nabla f)^k)(x) \preceq \lambda^k I$$

and so

$$0 \prec (1 - \lambda^k) I \preceq J(\nabla h_k)(x) \preceq (1 + \lambda^k) I.$$

The remaining parts of the lemma are proved in an analogous way using Proposition 1 and basic algebraic manipulations. □

B.7 Proof of Theorem 3

Proof. By Assumption 1, for $c = 1, \dots, C$, there is some function h_c such that $\nabla h_c = (I - \gamma \nabla f_c)^k$. We can then define $q_c : \mathbb{R}^n \to \mathbb{R}$ by

$$q_c(x) := \frac{1}{2}\|x\|^2 - h_c(x).$$

By construction, $\nabla q_c = I - (I - \gamma \nabla f)^k$, so that $V_s = C^{-1} \sum_{c=1}^{C} \nabla q_c$. Therefore, $V_s = \nabla f_s$ where $f_s = C^{-1} \sum_{c=1}^{C} q_c$. The smoothness of any f_s such that $V_s = \nabla f_s$ follows directly from Lemma 1. □

C Closed Integral Curves in Federated Learning

In this appendix we present calculations that demonstrate the possibility of closed integral curves in federated learning with nonconvex client losses. The existence of losses of higher regularity than those presented here (e.g. convex or satisfying the PL condition) whose server dynamics admit closed integral curve solutions are an interesting open question. We suspect that examples like this can be transferred to some higher regularity classes, but clearly not all–e.g. [3] demonstrates that such cyclic examples are impossible for quadratic functions.

Our example dynamics take place in $\mathbb{R}^2$, and we focus on the case where we have $C = 2$ clients. For $c = 1, 2$ we define a family of functions by

$$f_c(x, y) := f_c^{(1)}(x, y) + f_c^{(2)}(x, y), \tag{12}$$

where

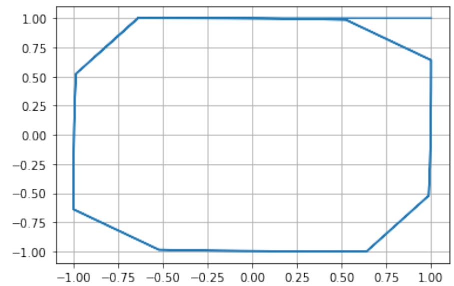
$$f_c^{(1)}(x, y) := \min\left(\frac{\alpha_c}{2}(y - y_c)^2 + \frac{\beta_c}{2}(x - x_c)^2, 1\right),$$

$$f_c^{(2)}(x, y) := \min\left(\frac{\alpha_c}{2}(y + y_c)^2 + \frac{\beta_c}{2}(x + x_c)^2, 1\right).$$

We will see that carefully selecting two functions from this family to represent two clients, and performing full-gradient FedAvg on these clients, will yield server dynamics with closed integral curves. First, note that for any x_c and y_c, α_c and β_c can be chosen such that the domains of attraction of the terms $f_c^{(1)}$ and $f_c^{(2)}$ are non-overlapping. One can verify that setting $\lambda = 5, \delta = 0.05$, and letting $\alpha_1 = \delta, \beta_1 = \lambda, x_1 = y_1 = 1, \alpha_2 = \lambda, \beta_2 = \delta, x_2 = -1, y_2 = 1$ satisfies this requirement. Let these choices define the functions f_1 and f_2.

Now, assume we perform FedAvg with fixed (client) learning rate $\gamma > 0$ for some sufficiently large number of local steps k. We assume these clients follow full gradient descent, and we choose k large enough so that the clients following full-gradient descent on the losses f_1 and f_2 converge to a stationary point, independent of starting point. This can be guaranteed in our setting by setting $k = O\left(\gamma^{-1}\right)$, with (easily computable) constant depending on λ and δ.

Figure 2: Trajectory of global model under FEDAVG, clients f_1 and f_2, $\gamma = 0.01, \eta = 1., k = \frac{4}{\gamma}$.



Notice that by assuming clients 'run until convergence', the form of the server vector field V_s (defined in (2)). becomes quite simple. We define the following domains in the xy-plane:

$$\begin{aligned} \mathbf{I} &= \{(x,y) : f_1^{(1)}(x,y) < 1\}, \\ \mathbf{II} &= \{(x,y) : f_1^{(2)}(x,y) < 1\}, \\ \mathbf{III} &= \{(x,y) : f_2^{(1)}(x,y) < 1\}, \\ \mathbf{IV} &= \{(x,y) : f_2^{(2)}(x,y) < 1\}. \end{aligned} \tag{13}$$

It is straightforward (though tedious) that our choices of λ, δ above ensure $\mathbf{I} \cap \mathbf{IV}, \mathbf{I} \cap \mathbf{III}, \mathbf{II} \cap \mathbf{III}$, and $\mathbf{II} \cap \mathbf{IV}$ are all nonempty. With these regions defined, a straightforward computation shows that the server vector field V_s for FEDAVG with $\eta = 1$ is given by:

$$V_s(x,y) = \begin{cases} (1-x,-y) & (x,y) \in \mathbf{I} \cap \mathbf{IV} \\ (-x, 1-y) & (x,y) \in \mathbf{I} \cap \mathbf{III} \\ (-1-x,-y) & (x,y) \in \mathbf{II} \cap \mathbf{III} \\ (-x,-1-y) & (x,y) \in \mathbf{II} \cap \mathbf{IV} \\ (1-x, 1-y) & (x,y) \in \mathbf{I} \cap (\mathbf{III}^c \cup \mathbf{IV}^c) \\ (-1-x, 1-y) & (x,y) \in \mathbf{III} \cap (\mathbf{I}^c \cup \mathbf{II}^c) \\ (-1-x,-1-y) & (x,y) \in \mathbf{II} \cap (\mathbf{III}^c \cup \mathbf{IV}^c) \\ (1-x,-1-y) & (x,y) \in \mathbf{IV} \cap (\mathbf{I}^c \cup \mathbf{II}^c) \\ 0 & \text{otherwise.} \end{cases} \tag{14}$$

We define a flow along this vector field in the usual manner, by the ODE

$$\frac{d}{dt}\left(x(t), y(t)\right) = V_s(x,y).$$

That the dynamics of FEDAVG will admit closed integral curves in this setup can now be readily seen, either by inspecting Fig. 1 or explicitly following a closed trajectory. The dynamics of FEDAVG (as in (1)) correspond to discretizing the ODE above with some step-size η. That is, FEDAVG corresponds to the stepping from (x_t, y_t) to $(x_{t+1}, y_{t+1}) := (x_t, y_t) + \eta V_s(x_t, y_t)$. Under this discretization, letting $(x_0, y_0) = (0, 1)$ and choosing $\eta = 1$ yields a closed trajectory of period 8. Further, the choice of discretization does not affect the nature of the closed curve, only its period, as is clear from Fig. 1. To emphasize this fact, we plot an observed trajectory of FEDAVG with client losses f_1 and f_2 as specified above, initialized at $(1, 1)$, in Fig. 2.